Comparison of static and dynamic resilience for a multipurpose reservoir operation

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Abstract

Reliability, resilience, and vulnerability are the traditional risk measures used to assess the performance of a reservoir system. Among these measures, resilience is used to assess the ability of a reservoir system to recover from a failure event. However, the time-independent static resilience does not consider the system characteristics, interaction of various individual components and does not provide much insight into reservoir performance from the beginning of the failure event until the full performance recovery. Knowledge of dynamic reservoir behavior under the disturbance offers opportunities for proactive and/or reactive adaptive response that can be selected to maximize reservoir resilience. A novel measure is required to provide insight into the dynamics of reservoir performance based on the reservoir system characteristics and its adaptive capacity. The reservoir system characteristics include, among others, reservoir storage curve, reservoir inflow, reservoir outflow capacity, and reservoir operating rules. The reservoir adaptive capacity can be expressed using various impacts of reservoir performance under the disturbance (like reservoir release for meeting a particular demand, socioeconomic consequences of reservoir performance, or resulting environmental state of the river upstream and downstream from the reservoir). Another way of expressing reservoir adaptive capacity to a disturbing event may include aggregated measures like reservoir robustness, redundancy, resourcefulness, and rapidity. A novel measure that combines reservoir performance and its adaptive capacity is proposed in this paper and named “dynamic resilience.” The paper also proposes a generic simulation methodology for quantifying reservoir resilience as a function of time. The proposed resilience measure is applied to a single multipurpose reservoir operation and tested for a set of failure scenarios. The dynamic behavior of reservoir resilience is captured using the system dynamics simulation approach, a feedback-based object-oriented method, very effective for modeling complex systems. The results of dynamic resilience are compared with the traditional performance measures in order to identify advantages of the proposed measure. The results confirm that the dynamic resilience is a powerful tool for selecting proactive and reactive adaptive response of a multipurpose reservoir to a disturbing event that cannot be achieved using traditional measures. The generic quantification approach proposed in the paper allows for easy use of dynamic resilience for planning and operations of various civil infrastructure systems.

1. Introduction

Dams are water storage, control, or diversion structures that basically impound water upstream in the reservoirs. Dams and reservoirs can significantly contribute to the economy of a country through the redistribution of flow in time and space for meeting various purposes like irrigation, hydropower generation, flood control, domestic and industrial water supply, water quality control, and recreation. They are one of the 18 critical infrastructures and key resources (CIKR) identified by the United States Department of Homeland Security [Vugrin et al., 2010] for reducing impacts from any natural or man-made disasters. They are essential civil infrastructure systems, but sensitive to failure due to system disturbances that may include events like floods, droughts, earthquakes, landslides, debris flow, improper functioning of sensors, supervisory control and data acquisition (SCADA) problems, icing of spillway gates, and failure of mechanical and electrical components. Dams are exposed to complex interaction of several individual components and various combinations of system disturbances. Dam and reservoir system failures may be divided into structural and functional [Hy, 1990]. Structural failures include collapse or breach of a dam, and/or failure of any of its structural, mechanical and/or electrical components that may be caused by a system disturbance. Structural failures may occur due to ageing of infrastructure, lack of maintenance, improper design, or construction error.
A functional failure happens when a dam or its components do not collapse, but the structure and reservoir behind it are not able to serve the intended purpose. These failures may be caused by improper operations, unexpected extreme natural conditions (floods and droughts), change in water demand, and similar. The examples of functional failures may include delayed opening of sluice gates for irrigation that may result in crop failure, untimely releases that may result in downstream flooding during the rainy season and others. Failures of large dams due to disturbances caused by undesirable events are of serious concern. They not only do cause loss of human lives and destruction of other infrastructure systems but may also be source of serious damage to the economy of a region. Therefore, greater emphasis needs to be given to reservoir system’s ability to prevent, withstand, and recover from a failure caused by an undesirable event.

Reliability, resilience, and vulnerability are the fundamental characteristics that define the state of any system and are widely used to assess the performance of the system. Among these indices, resilience refers to the systems capability to respond, withstand, and recover from a failure. The concept of resilience was first introduced by Holling [1973] in ecological systems and defined as the measure of ability of the system to absorb changes and still persist with the same basic structure when subject to stress. Later, in the widely accepted work, Hashimoto et al. [1982] extended the application of resilience to water resources systems and reported that reliability, resilience, and vulnerability are the potential measures to evaluate the performance of a reservoir system. They defined resilience as the measure that describes how quickly a system will recover, or bounce back, from failure once failure has occurred. Since the work of Hashimoto et al. [1982], the concept of resilience evolved and has been widely used in reservoir systems [Kjeldsen and Rosbjerg, 2004]. However, the traditional resilience measure (introduced by Hashimoto et al. [1982] and expanded by others) has some limitations. It is a static (time-independent) probabilistic measure based on a number of events (i.e., satisfactory state following an unsatisfactory state). Therefore, it does not consider the actual impact and dynamics of a disruptive event. McMahon et al. [2006] reported that this resilience index results in the same value for different failure events. The traditional performance measures (reliability, resilience, and vulnerability) are mostly used for assessing the functional failures of reservoir systems. However, complex reservoir systems (including dam/s, mechanical, electric, and human components) are exposed to various hazards and thus have a variety of ways in which they can fail. Understanding complex behavior of these systems during a disruptive event may provide a lot of information for selecting appropriate adaptation measures (both, proactive and reactive).

The complex interactions of several individual components and unusual combinations of various (usual) disruptive events possess serious threat to reservoirs and dam safety. Some of the dam failures include overtopping, spillway cavitation, penstock failure, embankment failure, and uncontrolled flow release [Regan, 2010; Komey et al., 2015]. It has been reported that various dam failure incidents are often a result of complex interactions between system components [Regan, 2010] and loss of reservoir control. The traditional resilience measure, as defined by Hashimoto et al. [1982], is not able to address complex interactions of various reservoir system components and failures that are caused by unusual combinations of various disruptive events (for example, high reservoir storage, high precipitation event, loss of electricity, and break in communications). The static resilience is merely an abstract attribute of the system that

1. does not capture the importance of system structure and inter relationships between system components,
2. does not capture interactions between system behavior and the disturbance event,
3. ignores complex dynamics of system response,
4. cannot assess how capable the system is to absorb the disruption,
5. cannot include the ability of the system to deliver partial level of service,
6. cannot capture the dynamics of the recovery process (conditioned on the ability to mobilize resources), and
7. cannot identify when the system will recover to normal functioning state.

In the dynamic context, last four characteristics of the reservoir system/s are called robustness, redundancy, resourcefulness, and rapidity [Bruneau et al., 2003]. The static resilience is not tailored to capture (i) consequences of various feedbacks within the complex reservoir system/s produced by interdependencies of system components, (ii) future unknown system states, and (iii) importance of spatial and temporal scales [Rosati et al., 2015].
While traditional static measures are more appropriate for assessment of predisturbance vulnerabilities, dynamic resilience is achieved by introducing adaptation options that enable the system to adapt to the impacts of the disturbance and enhance the ability of its components to function during the disturbance. These adaptation options help the system components to cope with and recover from disturbing event in order to return to a predisturbance level of performance as rapidly as possible. Adaptation options can be grouped into four categories: (i) robustness that is the strength or the ability of the system to resist disturbance-induced stresses (e.g., spillway capacity); (ii) redundancy that is the ability of a system to provide uninterrupted services in the event of a disruption (e.g., a twinned water supply pipeline); (iii) resourcefulness that is the utilization of materials (monetary, technological, informational, and human resources) to establish, prioritize, and achieve operational goals (e.g., SCADA system used by reservoir operators); and (iv) rapidity that is the capacity to return the system to a predisturbance level of functioning as quickly as possible. Evidently, dynamic resilience is a proactive means of reservoir system management making it more desirable for practical implementation.

Generic presentation of system performance used for the quantification of dynamic resilience is shown in Figure 1. The solid line in Figure 1 represents the consequence of integrated system performance under the disturbing event with current system adaptation capacity. The slope of the declining section (represented for time \( t_0 < t < t_1 \) by \( SP_{t_1} - SP_{t_0}/t - t_0 \)) of the performance curve provides insight into system redundancy and slope of the rising section (represented for time \( t_1 < t < t_r \) by \( SP_{t_r} - SP_{t_1}/t - t_1 \)) of the performance curve offers the information about system resourcefulness. Robustness of the system and rapidity are clearly illustrated with the system performance level at time \( t_1 \) and difference in time between \( t_0 \) and \( t_r \), respectively. Implementation of various adaptation measures results in the change of the shape of the performance curve (two examples are shown in Figure 1 using dashed lines). For example, proactive measures will result in curve (a) and reactive measures may results in curve (b). This interpretation of the system performance is already clearly illustrating the benefits of dynamic resilience over traditional static definition. Simonovic and Peck [2013] demonstrated some of these advantages in the context of climate change caused flood management.

The definition of dynamic resilience evolved from ecology-based “the ability of a system to withstand stresses of 'environmental loading'” [Holling, 1973], over hazard-based “the capacity of a system, community, or society potentially exposed to hazards to adapt, by resisting or changing, in order to reach and maintain an acceptable level of functioning and structure” [for example, Bruneau et al., 2003], to the one proposed by Simonovic and Peck [2013] “the ability of an infrastructure system and its component parts to anticipate, absorb, accommodate or recover from the effects of a system disruption in a timely and efficient manner, including through ensuring the preservation, restoration or improvement of its essential basic structures and functions” which is adopted in the presented work. The dynamic measure of resilience requires knowledge of various system components, their interactions, disturbances, and ability to continuously adapt and
change throughout the disturbance event at multiple spatial and temporal scales [Park et al., 2013]. It is apparent that the need for the integration of dynamic resilience into planning, design, and operations of reservoirs. Sufficient literature is available on the conceptualization of disaster resilience [Bruneau et al., 2003; Cutter et al., 2008]. More recently, however, researchers have found merit in defining resilience quantitatively [Bruneau et al., 2003; Vugrin et al., 2010; Aven, 2011; Henry and Ramirez-Marquez, 2012; Ayyub, 2015]. A very few studies have considered describing resilience using system adaptation characteristics [Bruneau et al., 2003; Pant et al., 2014]. Most of the proposed approaches are estimating the resilience as a time-independent measure and do not provide much insight about the recovery capability of the system over time.

Simonovic and Peck [2013] first developed a framework to quantify the dynamic resilience through system dynamics simulation in the context of adaptation to changing climatic conditions. System dynamics (SD) simulation is one of the tools that can assist the decision makers in understanding the dynamic behavior of complex systems, thereby enabling a more integrated approach to enhance their performance and increase their resilience. No study has been reported on estimating the resilience of a multipurpose reservoir in the system dynamics simulation context subject to different disturbance events.

The main objectives of the present study are to (i) implement for the first time definition of dynamic resilience to multipurpose reservoir management under disturbance; (ii) explore the utility of SD simulation as a tool for quantifying the dynamic resilience of a multipurpose reservoir management in the event of multiple (consecutive) disturbances of different nature; and (iii) identify advantages of a new resilience measure by comparing traditional (static) resilience and the dynamic reservoir resilience. The novelty of the proposed dynamic resilience measure is that it is built on the robustness, redundancy, resourcefulness, and rapidity characteristics of the reservoir system, which capture the actual behavior (system performance) of the reservoir and its adaptive capacity subject to any disturbance. The proposed dynamic resilience can be assessed for various reservoir system components individually, as well as for the overall reservoir system. The dynamic resilience of individual system components is estimated based on performance of various components and the system resilience integrates resilience of various components together after normalization.

The rest of the paper is organized in the following manner. The concepts of traditional measures and dynamic resilience are explained in the methodology section. The implementation of the dynamic resilience using system dynamics simulation for a single multipurpose reservoir is then discussed. The application of dynamic resilience to a case study and the results of comparison with the traditional measures for different failure scenarios are then reported. Finally, the various merits of the dynamic resilience are summarized in the conclusions section.

2. Methodology

2.1. Traditional Reservoir System Performance Measures

Generally, the performance of the reservoir system is assessed by simulating the behavior of the system and estimating the reliability (used as a risk indicator), resilience, and vulnerability. These measures give the overall picture of the system performance for various operating conditions. Reliability ($r$) is the probability of the reservoir system being in nonfailure state during the simulation period [Hashimoto et al., 1982]. Let us consider a reservoir that provides water for meeting the irrigation demand. The period during which the reservoir system is able to meet the demand is called success state (SS), and the period during which the reservoir system could not satisfy the demand is the failure state (F) (system disturbance). Let $X_t$ be the state of the reservoir system at time $t$ that takes the binary value 0 or 1, where 0 denotes the failure state and 1 is the success state. Then, the state of the system at any time $t$ is represented as

$$X_t=\begin{cases} 1, & \text{if } R_t \geq D_t \\ 0, & \text{otherwise} \end{cases}$$

where $R_t$ is the release made from the reservoir during the time period $t$ and $D_t$ is the demand during the time period $t$. The reliability of the system (i.e., the probability of the system in success state, $\alpha = P[X_t \in SS]$) is given as
where $T$ is the total simulation time period.

Resiliency ($\gamma$) describes how quickly a system is likely to recover or bounce back from failure once failure has occurred. Hashimoto et al. [1982] measured it as the conditional probability of a success state following a failure state. It is represented as

$$\gamma = \{X_{t+1} \in SS | X_t \in F\}$$

This measure is also equal to the inverse of the mean value of the time the system spends in the failure state [Kjeldsen and Rosbjerg, 2004]. It can also be estimated by [Loucks, 1997; McMahon et al., 2006]

$$\gamma = \frac{M}{M_d}$$

where $M$ is the number of individual continuous sequences of failure events and $M_d$ is the total duration of all the failure events.

The extent of the failure event is measured through vulnerability. Hashimoto et al. [1982] defined vulnerability ($\nu$) as a measure of the likely magnitude of a failure event and is given as

$$\nu = \sum_{j=1}^{M} s_j e_j$$

where $s_j$ is the most severe outcome of the $j$th sojourn in unsatisfactory state and $e_j$ is the probability of $s_j$ being the most severe outcome of a sojourn into the unsatisfactory state. The probability of each failure event is equal, i.e., $e_1 = \ldots = e_M = 1/M$, where $M$ is the number of failure events. Therefore, vulnerability can be estimated as the mean value of the deficit events [Loucks, 1997; Kjeldsen and Rosbjerg, 2004] and is given as

$$\nu = \frac{\sum_{j=1}^{M} \nu_j}{M}$$

where $\nu_j$ is the deficit during the failure event $j$ and $M$ is the total number of failure events. Thus, the vulnerability averages the total deficit during the simulation period. A reduction in number of failure events for the same total deficit increases the vulnerability of the system. This may occur when the reservoir capacity is increased with all other factors being the same [McMahon et al., 2006].

### 2.2. Reservoir Dynamic Resilience

The quantitative dynamic resilience measure, first introduced by Simonovic and Peck [2013] following Cutter et al. [2008], has two qualities: inherent (functions well during nondisturbance periods) and adaptive (flexibility in response during disturbance events) and can be applied to physical environment (built and natural), social systems, governance network (institutions and organizations), and economic systems (metabolic flows). An original space-time dynamic resilience measure (STDRM) of Simonovic and Peck [2013] is designed to capture the relationships between the main characteristics of resilience; one that is theoretically grounded in systems approach, open to empirical testing, and one that can be applied to address real-world problems in various domains. The following is mathematical derivation of multipurpose reservoir dynamic resilience.

STDRM is based, as previously stated, on two basic concepts: level of reservoir system performance and system adaptive capacity. They together define reservoir system performance. Figure 2 illustrates the reservoir performance under disturbing event (for example reservoir performance can be expressed in flow units (m$^3$/s) capturing reservoir release for hydropower production).

The area between the initial performance line $P_0$ and performance line $P(t)$ represents the loss of system performance, and the shaded area under the performance line $P(t)$ represents the system resilience. In Figure 2, $t_0$ denotes the beginning of the disturbance, $t_1$ the end, and $t_2$ the end of the recovery period. There are three possible outcomes in resilience simulation: (i) resilience returns to predisturbance level (value of 1)—solid line in Figures 2 and 3; (ii) resilience exceeds predisturbance level (ending system
performance level $P_e(t)$, resilience value $> 1$—dashed line in Figures 2 and 3; or (iii) resilience does not return to predisturbance level (ending system performance level $P_e(t)$, value $< 1$)—dashed and dotted line in Figures 2 and 3.

In mathematical form, the loss of performance $q(t)$ represents the area in Figure 2 between the beginning of the system disruption event ($t_0$) and the end of the disruption recovery process ($t_r$). It can be obtained mathematically as

$$ q(t) = \int_{t_0}^{t_r} [P_0 - P(t)] \, dt, \quad \text{where} \ t \in [t_0, t_r] \tag{7} $$

where $P(t)$ represents measure of system performance and $P_0$ is the initial system performance level.

The system resilience, $r(t)$ is then calculated by normalizing the value of $(\rho)$ as follows:

$$ r(t) = 1 - \frac{\rho(t)}{P_0 \times (t - t_0)} \tag{8} $$

which eliminates the units of system performance and replaces them with units of resilience between 0 and 1 (see Figure 3 for representation of resilience).
The calculation of STDRM is done for each point in time by solving the following differential equation using system dynamics simulation:

$$\frac{\partial R(t)}{\partial t} = AC(t) - P(t)$$  \hspace{1cm} (9)

where AC stands for adaptive capacity. Adaptive capacity is defining the shape of the resilience curve through the four values of robustness, redundancy, resourcefulness, and rapidity. Robustness is mathematically expressed as the minimum value of the remaining system performance after the disruption; redundancy is defined as the slope of the declining section of resilience graph; resourcefulness is calculated as the slope of the recovery section of the resilience line; and rapidity is defined as the time difference between the t₀ and t₁ (duration of system performance affected by the disturbance). They are all shown in Figure 3. Various adaptation options result in different values of these system characteristics.

As illustrated in Figure 2, performance of a system which is subject to a disturbance event drops below the initial value and time is required to recover the loss of system performance. Disturbance to a system causes a drop in system resilience from value of 1 at t₀ to some value r(t₁) at time t₁, see Figure 3. Recovery usually requires longer time than the duration of disturbance. Ideally resilience value should return to a value of 1 at the end of the recovery period, tₐ (solid line in Figure 3); and the faster the recovery, the better. There are three possible outcomes in resilience simulation: (i) resilience returns to predisturbance level (value of 1)—solid line in Figures 2 and 3; (ii) resilience exceeds predisturbance level (value > 1)—dashed line in Figures 2 and 3; or (iii) resilience does not return to predisturbance level (value < 1)—dashed and dotted line in Figures 2 and 3.

Reservoir problems, as many water resources management problems, have important spatial dimension. Therefore, the above quantification of dynamic resilience is further expanded to include variability of system performance in space, by modifying equations (7)–(9) to indicate the change of resilience value with location in space, s:

$$\rho(t,s) = \int_{t_0}^{t} [P_0 - P(t,s)] dt \text{ where } t \in [t_0, t_1]$$  \hspace{1cm} (10)

$$r(t,s) = 1 - \left( \frac{\rho(t,s)}{P_0 \times (t-t_0)} \right)$$  \hspace{1cm} (11)

$$\frac{\partial R(t,s)}{\partial t} = AC(t,s) - P(t,s), \ t \in [t_0, t_1]$$  \hspace{1cm} (12)

The level of system performance can integrate various impacts (i) of reservoir disturbance. The following impacts (units of resilience (ρ')) can be considered: physical, economic, health, social, and organizational, but the general measure is not limited to them. Measure of system performance P'(t, s) for each impact (i) is expressed in the impact units (physical impact may include for example reservoir storage that has to be provided (m³) for incoming flood attenuation; health impact may be measured using an integral index like disability adjusted life year or something simpler like number of people affected by the reservoir water carrying disease; and so on). This approach is based on the notion that an impact, P'(t, s), which varies with time and location in space, defines a particular resilience component of a system under consideration.

In mathematical form, the loss of resilience for impacts (i) represents the area under the performance graph between the beginning of the system disruption event at time (t₀) and the end of the disruption recovery process at time (t₁). Changes in system performance can be represented mathematically as

$$\rho'(t,s) = \int_{t_0}^{t} [P'_0 - P'(t,s)] dt \text{ where } t \in [t_0, t_1]$$  \hspace{1cm} (13)

When performance does not deteriorate due to disruption, P₀'(t, s) = P'(t, s) the loss of resilience is 0 (i.e., the system is in the same state as at the beginning of disruption). When all of system performance is lost, P'(t, s) = 0, the loss of resilience is at the maximum value. The system resilience, r'(t, s) is calculated as follows:
As illustrated in Figure 2, performance of a system which is subject to a disaster event drops below the initial value and time is required to recover the loss of system performance. Disturbance to a system causes a drop in system resilience from value of 1 at \( t_0 \) to some value \( r'(t, s) \) at time \( t_1 \), see Figure 2. Recovery usually requires longer time than the duration of disturbance. Ideally resilience value should return to a value of 1 at the end of the recovery period, \( t_r \) (dashed line in Figure 3); and the faster the recovery, the better. The system resilience \( R \) (over all impacts \( i \)) is calculated using:

\[
R(t, s) = \left( \prod_{i=1}^{M} r'(t, s) \right)\text{M}
\]

where \( M \) is total number of impacts.

The calculation of STDRM for each impact \( i \) is done at each location \( s \) by solving the following differential equation:

\[
\frac{\partial r'(t)}{\partial t} = AC(t) - P(t)
\]

where \( AC_i \) represents adaptive capacity with respect to impact \( i \). The dynamic system resilience that integrates various impacts of reservoir system under consideration \( i \) is calculated at each location in space \( s \) using:

\[
\frac{\partial R(t)}{\partial t} = AC(t) - \sum P(t)
\]

The dynamics of the resilience is captured through system dynamics simulation approach. System dynamics (SD) simulation was developed based on the control theory and has evolved into a widespread approach for modeling complex dynamic nonlinear systems. It is a rigorous object-oriented simulation approach, which can be used in the analysis of difficult real-world problems [Simonovic, 2009]. The strength of the SD approach is in modeling complex nonlinear feedback systems over time, where the change in the system state variables due a decision is internalized within a feedback loop. Thus, SD simulation allows the modeler to observe the behavior of a system and its response to any disturbance over time. The transparency of SD simulation enhances the understanding of the links between the system structure and its dynamic behavior through interaction and relationships among the different elements of the structure.

The SD model for calculation of reservoir system resilience is developed in such a way that multiple disturbances during the simulation are effectively handled and captured. To start with, the initial failure time \( t_0 \) is assumed as zero. Once the system encounters a disturbance event and change in system performance is observed, the system state changes from normal operating state to failure state. Then, the failure time is updated to the simulation time at which the change of system state occurred and made constant until next failure event. In case of multiple disturbance events, the initial failure time \( t_0 \) is updated at the start of every failure event, as shown in Figure 4. For example, the first failure event occurred at point \( A \) in Figure 4 and the corresponding time \( t_0 \) of event is set as failure time \( t_0 \). When the second failure is encountered at point \( B \).
during the simulation, then the failure time $t_f$ is updated to the time of point $B$. Accordingly, the change in system performance is estimated for each impact (performance measure) and the dynamic resilience is computed.

The calculation of STDRM in space requires integration of the system dynamics simulation model with a spatial analysis tool, like GIS, that allows for the presentation of the results in the form of dynamic maps. The computational process (temporal simulation) is performed for each spatial unit using the SD simulation software. Since the calculated value of $R(t,s)$ will change with time and location, the final outcome of the STDRM computation is a dynamic map that shows change of $R(t,s)$ with time and location. Selected spatial resolution of analysis may require aggregation and/or disaggregation of indicators selected for description of various impacts, (i). Discussion in the paper and the case study of Koyna reservoir are not extended to spatial implementation of dynamic resilience which can be found in Simonovic and Arunkumar [2016].

Based on the mathematical definition of dynamic resilience, Table 1 provides a basic comparison between traditional resilience and dynamic resilience.

### Table 1. Comparison of Traditional Measure of Resilience and Dynamic Resilience

<table>
<thead>
<tr>
<th>Traditional Resilience</th>
<th>Dynamic Resilience</th>
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</thead>
<tbody>
<tr>
<td>Measure is estimated in probabilistic form after the simulation of the behavior of the system over the time horizon</td>
<td>It is estimated during the simulation itself (at each time $t$)</td>
</tr>
<tr>
<td>Measures remains the same for different type of failure events</td>
<td>For different failure events, dynamic resilience varies based on the impact of the event</td>
</tr>
<tr>
<td>System adaptation characteristics such as robustness, redundancy, resourcefulness, and rapidity are not considered</td>
<td>Within simulation provides all characteristics of system adaptive capacity: robustness, redundancy, resourcefulness, and rapidity</td>
</tr>
<tr>
<td>Cannot be used in real time for decision making</td>
<td>Can be used in real time to evaluate both, proactive and reactive adaptation measures</td>
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#### 3. Case Study

The developed dynamic resilience methodology is applied to a multipurpose reservoir, namely Koyna Hydro Electric Project (KHEP) in Maharashtra, India. The case study analysis is performed to (a) illustrate the implementation of the dynamic resilience method to a multipurpose reservoir; (b) provide for the comparison between the traditional performance measures (reliability, resilience, and vulnerability) and the dynamic resilience; and (c) point out how dynamic resilience can be used for multipurpose reservoir planning design and operations. The Koyna reservoir is already in operations and no system failure events are recorded. Direct use of the analyses results will not be implementable by the operators of the reservoir. However, the dynamic resilience measure and methodology presented here can assist in the evaluation of possible proactive measures like maintenance planning, emergency operations, adaptation of operating rules to changing natural (inflow, evaporation, etc.) and socio economic conditions (demand for power, demand for irrigation, population growth, etc.), demand management, and similar.

#### 3.1. System Description

The Koyna is one of the largest hydropower reservoirs in India, which serves for both, hydropower production and irrigation water supply. The catchment area and location of Koyna dam is shown in Figure 5. The catchment is elongated, hilly with steep slopes with an area of about 891.78 km$^2$. The average annual rainfall is about 5000 mm and this water is impounded by the Koyna Dam. The total storage capacity of the reservoir is $2797.40 \times 10^6$ m$^3$. The Koyna dam has three powerhouses, two on the western side in underground, and one on the eastern side at the dam foot. Although Koyna dam is primarily built for generating hydropower, it also serves irrigation purposes like most of the other dams in the Indian subcontinent. The irrigation outlets are on the eastern side of the reservoir, which has fertile land as compared to barren exposed rock covers, and undulating terrain on the western side, where the major powerhouses are located. All the underground powerhouses in the western side are peak stations and operated only for meeting the peak power demand. However, the power production at the dam foot powerhouse is incidental, generates hydropower only through irrigation releases. Therefore, the releases through these powerhouses are considered as irrigation releases and not as power releases. More details about the reservoir system can be found in Arunkumar and Jothiprakash [2012]. Ten years of historical daily inflow (from 1 June 2000 to 31
May 2010) observed at the dam was collected and used in simulation. The time series of reservoir inflow is shown in Figure 6. Analysis of inflow data shows that the inflow is intermittent and the reservoir receives inflow only during the monsoon season. Inflow during the nonmonsoon season is negligible. Data on Koyna reservoir system failures in the past, if any, are not available. Therefore, in the case study section, we developed four potential failure scenarios for the illustration of the methodology discussed in the paper.

3.2. SD Simulation Model Development
The dynamic resilience of a multipurpose reservoir is quantified for different disturbance events using SD simulation approach. To achieve this, the operations of the multipurpose reservoir and its dynamic resilience are modeled using Vensim package—a SD simulation software [Vensim, 2014]. The first step in SD simulation modeling is to determine the system structure consisting of positive and negative feedback relationships between variables, and delays represented through a causal loop diagram [Simonovic, 2009]. Two simulation modules are structured within the Vensim for the purpose of this study, one for the simulation of multipurpose reservoir operation and the other for quantitative dynamic resilience calculation. The development and structure of two simulation modules are discussed in the following section. Reservoir operation simulation results are used for the calculation of traditional performance measures as well as the dynamic resilience computation.

3.2.1. Multipurpose Reservoir Simulation Module
The multipurpose reservoir SD simulation module is shown in Figure 7 using stock and flow representation. It simulates the operations of the reservoir for irrigation and hydropower production using standard operating policy. The reservoir operation model consists of the continuity equation and a set of other operational constraints. The continuity equation is expressed as
\[ S_t = S_{t-1} + I_t - TR_t - O_t - SP_t \]  \hspace{1cm} (18)

where \( S_t \) is the storage at the time period \( t \) (\( 10^6 \text{ m}^3 \)); \( S_{t-1} \) is the reservoir storage at the beginning of time period \( t \) (\( 10^6 \text{ m}^3 \)); \( I_t \) is the inflow during the time period \( t \) (\( 10^6 \text{ m}^3 \)); \( TR_t \) is the total release made from the reservoir, which includes power release (\( PR_t \)) and irrigation release (\( IR_t \)) during the time period \( t \) (\( 10^6 \text{ m}^3 \)); \( O_t \) is capturing the evaporation and other leakage losses from the reservoir (\( 10^6 \text{ m}^3 \)); and \( SP_t \) is the spill from the reservoir during the time period \( t \) (\( 10^6 \text{ m}^3 \)). The system constraints, reservoir operating rules, and the release decisions are captured using IF-THEN-ELSE statements in the simulation model. If the available reservoir
storage is greater than the demand (power or irrigation), then the actual demand is released; else the available storage is released.

According to Loucks et al. [1981], the hydropower production \( (P_t) \) during any time period \( t \) in terms of kilowatt-hours (kWh) from the reservoir is expressed as

\[
P_P = K \times P_R + \eta \times (E_t - E_T)
\]

(19)

where \( P_P \) is the power generation during the period \( t \); \( P_R \) is the power release during the period \( t \) \((10^6 \text{ m}^3)\); \( E_t \) is the average water level elevation in the reservoir during the time \( t \) (m); \( E_T \) is the tailwater elevation (m); \( \eta \) is the efficiency of the turbine and \( K \) is the constant for converting the product of release, net head and efficiency into power (kWh).

In the reservoir model, turbine disturbance event is considered to represent the scenario of structural failure of the system. It is modeled as a binary variable, which takes the value of 0 or 1. Upon failure, the variable takes the value 0 and makes the power release equal to 0.

The dynamic resilience calculation utilizes various impacts of reservoir performance under the disturbance. The Koyna reservoir dynamic resilience is based on the two main impacts \( i \) of reservoir disturbance on power production \( (i = 1) \) and irrigation water supply \( (i = 2) \). The dynamic resilience is estimated through the analysis of system performance and integrated after normalization for the representation of the reservoir system resilience. The system performance for hydropower \( (P_1(t)) \) is expressed as the ratio of actual power release and the power demand during the time \( t \).

\[
P_1(t) = \frac{P_R}{P^{\text{demand}}_R}
\]

(20)

where \( P_R \) is the reservoir power release during the time \( t \), and \( P^{\text{demand}}_R \) is the power demand during the time \( t \). Similarly, meeting the irrigation demand is considered as the second measure of reservoir system performance \( (P_2(t)) \) for meeting the irrigation needs. It is expressed as

\[
P_2(t) = \frac{I_R}{I^{\text{demand}}_R}
\]

(21)

where \( I_R \) is the reservoir irrigation release during the time \( t \), and \( I^{\text{demand}}_R \) is the irrigation demand during the time period \( t \). These two performance measures are used for quantifying the dynamic resilience for different disturbance events.

### 3.2.2. Dynamic Resilience Simulation Module

Peck and Simonovic [2013] demonstrated the computation of dynamic resilience in the context of climate change caused flooding. However, their study quantified the dynamic resilience only for a single disturbance event occurring at the start of the simulation. Their work addresses neither the reservoir operations context nor potential multiple (consecutive) disturbance events during the simulation process. In the present study, variation of multipurpose reservoir dynamic resilience for multiple failure events at any time during the simulation is captured. Schematic of the dynamic resilience simulation module is depicted in Figure 8 using SD stock and flow representation.

The level of system performance for each impact estimated by the reservoir operation module is used here for quantifying the dynamic resilience. The **change in system performance** is represented as a stock (see Figure 8), since it accumulates the loss of system performance due to any disturbance over time. The failure time is represented by two variables, **failure time** and **initial failure time**. These two variables depend on each other and will be updated for successive failure events. As stated earlier, the **initial failure time** (beginning of the disturbance event) is assumed as zero at the start of simulation and changes when the system observes change of state due to any disturbance. The change of system state is obtained by comparing the level of system performance at every time step with the initial performance level. When there is a change in system performance level due to any disturbance, the failure time is updated to simulation time. Thus, these two variables are solved simultaneously through continuous iteration until no change is observed in the feedback loop.

In case of successive events, both the stock (change in system performance) and failure time are updated for every event. Stocks are computed from the beginning of the simulation and they accumulate over time.
However, for the second event, the change in system performance has to be estimated from the failure time and not from the beginning of simulation. Hence, an additional variable “change in system performance in previous time step” is used to deduct the accumulated stock until the previous time step and the updated value of stock is used to estimate the dynamic resilience for consecutive failure events. This is one time step delayed function of stock variable “change in system performance” in Figure 8. Initially, the deduction variable will be zero and updated for the successive failure events, similar to failure time. Finally, the dynamic resilience for each impact and overall system resilience are computed using equations (16) and (17), respectively.

4. Results and Discussion

The developed multipurpose reservoir simulation model is simulated for different disturbance events after thorough verification and testing of its ability to evaluate the state of the system for different conditions. The multipurpose reservoir operation is simulated for 10 years using a daily time step. The system behavior for different disturbance events and variation of dynamic resilience for each failure event is recorded. The traditional performance measures, such as reliability, resilience, and vulnerability, are also calculated. Both impacts, hydropower and irrigation, are evaluated using the level of performance measures expressed by equations (20) and (21). For both impacts, the performance measures are defined as the ratios of actual releases to the demand that range between zero and one. The measures are selected in the same form in order to give equal weight and to avoid any bias in estimating the overall reservoir system resilience. Because of nonavailability of data about the historical disturbance events, we assume two events that can
illustrate structural and functional failures. Often, functionality of certain components may not be available for normal operation due to repair, maintenance, breakout, etc. This has been represented by turbine failure scenario, which assumes that power production is interrupted (not available) due to unavailability of certain mechanical and/or electrical components. Failure to meet the demand for water from a reservoir is very common due to the uncertain intermittent reservoir inflow and ever increasing demand. Therefore, failure to meet the irrigation demand is used to illustrate the functional failure. The utility of the dynamic resilience is demonstrated for a multipurpose reservoir for these two types of disturbance events. The advantages of the dynamic resilience are highlighted through the comparison of dynamic resilience with the traditional performance measures. The results obtained from the simulation for different failure scenarios are discussed in the following four sections.

4.1. Scenario 1: No Failure Scenario
Initially, the Koyna reservoir model is simulated without any disturbance events (Scenario 1) in order to verify the model. As expected, the model perfectly captures the behavior of the system and the level of performance is not disturbed. Therefore, the resilience value remains equal to 1 throughout the simulation period for both, hydropower and irrigation purposes.

4.2. Scenario 2: Single Failure Event (One Turbine Failure Event)
In Scenario 2, a turbine disturbance event is considered during the simulation. This scenario illustrates a potential structural failure of power plant mechanical and/or electrical equipment. It is assumed that turbine function is not available for 200 days, from time period 501 to 700, during the simulation. Hence, the power release is 0 during this period. This results in plenty of available water in the reservoir, which completely meets the irrigation water demand. Therefore, there is no irrigation failure in this scenario. The dynamics of the resilience under the impact of single disturbance event for each measure of system performance are given in Figure 9. It can be seen (Figure 9a) that the power resilience drops to 0 at time 500 and remains

![Figure 9. Variation of dynamic resilience for a single failure event.](image-url)
zero during the duration of disturbance event (200 days). The graph in Figure 9a shows that the redundancy of the system is 0, as there is no substitute arrangements to continue the power production. The system performance at the failure time drops from full to 0. The reservoir robustness is equal to 0 too, since there is no alternative ways for any power production in the case of this failure. When the equipment is brought back to functioning state (day 700), the power production resumes and the power resilience gradually increases and attains a stable state at day 1714. Therefore, the power rapidity in this scenario is equal to 1514 days. The power robustness is equal to 1 since the power production is back and system is out of failure state. Average slope of rising resilience curve at any time $t$ provides the value of resourcefulness. Figure 9c is obtained by combining the power and irrigation resilience using equation (15). The difference between Figures 9a and 9c are pointing out one of the advantages of dynamic resilience over traditional performance measures by showing the impact of various system components on the overall system resilience. Figure 9c shows a faster system recovery and attains the stable state at day 1162. Therefore, the rapidity of the reservoir system is 962 days. The trajectory of the resilience depends on the resourcefulness which is one of the descriptors of reservoir adaptive capacity. Information obtained from Figure 9 is summarized in the dynamic resilience section of Table 2 for $t = 800$. It is important to point that that the dynamic resilience values are available for every time step whereas traditional measures do not change with time.

The traditional performance measures for this single failure event are given in Table 2. They show that the reliability of the reservoir is high, but the resilience is very low. Comparing these measures with dynamic resilience, it can be observed that the traditional measures do not properly account for the interaction of the individual components. The values of the performance measure remain the same for power and full system. The impact of the irrigation is not reflected in the overall system measures. Figure 9c shows the dynamic resilience of the reservoir system, which integrates the impact of both, power and irrigation. It can be seen that the dynamic resilience of power and reservoir differs. This can also be observed from Table 2. The reservoir system shows a higher resilience, when compared to the resilience of the power alone. The dynamic resilience value can be provided for any time $t$, providing users with the complete insight in the response of the reservoir to the turbine failure event. The values in Table 2 are provided only for $t = 800$.

### 4.3. Scenario 3: Consecutive Failure Events of the Same Type (Two Turbine Failure Events)

In Scenario 3, two turbine disturbance events are considered during the simulation to illustrate the variation in reservoir dynamic resilience for consecutive disturbance events. The first disturbance is introduced at time 501, followed by a second event at 1001, each for a period of 200 days. Thus, this scenario illustrates the events of consecutive structural failures. The variation of dynamic resilience for the consecutive disturbance events is shown in Figure 10. The power release is not available during the disturbance periods and the power production is 0. The power resilience drops twice to 0 at the start of each disturbance event and remains at 0 during the duration of disturbance period. The sudden drop in resilience shows that the redundancy of the system is zero, as there is no alternative arrangement to continue with power production. The power resilience gradually increases when the production is resumed and attains a steady state at day 1977. It is to be noted that the second disturbance event occurs before the full recovery of the system from the first event. The rapidity value of power production is 777 days. The reservoir system recovers faster and attains stable performance at day 1545. Therefore, the rapidity of the reservoir system is 345 days.

<table>
<thead>
<tr>
<th>System Component</th>
<th>Reliability</th>
<th>Resilience</th>
<th>Vulnerability (Mm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>0.9452</td>
<td>0.005</td>
<td>1000.00</td>
</tr>
<tr>
<td>Irrigation</td>
<td>1.00</td>
<td>Undefined</td>
<td>0.00</td>
</tr>
<tr>
<td>Reservoir</td>
<td>0.9452</td>
<td>0.005</td>
<td>1000.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dynamic Resilience (t = 800 Days)</th>
<th>Resilience</th>
<th>Robustness</th>
<th>Rapidity</th>
<th>Resourcefulness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>0.33</td>
<td>1.00</td>
<td>600</td>
<td>0.0040</td>
</tr>
<tr>
<td>Irrigation</td>
<td>1.00</td>
<td>1.00</td>
<td>600</td>
<td></td>
</tr>
<tr>
<td>Reservoir</td>
<td>0.58</td>
<td>1.00</td>
<td>600</td>
<td>0.0093</td>
</tr>
</tbody>
</table>
of system components at day 1500 extracted from Figure 10 is given in Table 3. The table also compares traditional performance measures and dynamic resilience for consecutive failure events. If we look at the traditional performance measures, comparison of Scenarios 2 and 3 shows slight decrease in reliability of the system due to multiple disturbance events. However, resilience and vulnerability remain the same. This shows that the traditional measures will give the same resilience value for multiple failure events, if the duration of the individual failure events is the same. Also, the traditional measures have the same value for both, power resilience and reservoir system resilience. The dynamic resilience values of individual system components are different from the reservoir system resilience. Results summarized in Table 3 show that the reservoir system exhibits a higher resilience compared to power resilience. The resourcefulness of the system is higher too, since it integrates impacts on both reservoir purposes, power generation and irrigation.

![Figure 10. Variation of dynamic resilience for two successive failure events of the same type.](image)

<table>
<thead>
<tr>
<th>System Component</th>
<th>Traditional Performance Measures</th>
<th>Dynamic Resilience (t = 1500 Days)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Reliability</td>
<td>Resilience</td>
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<tr>
<td>Power</td>
<td>0.8905</td>
<td>0.005</td>
</tr>
<tr>
<td>Irrigation</td>
<td>1.000</td>
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</tr>
<tr>
<td>Reservoir</td>
<td>0.8905</td>
<td>0.005</td>
</tr>
</tbody>
</table>
water supply. As in the previous case, the main advantage of dynamic resilience as compared to traditional resilience is in the complete description of the reservoir response to two turbine failure events at any moment in time.

4.4. Scenario 4: Multiple Failure Events of Different Types

In Scenario 4, one turbine and two other disturbance events, (i) inability of the reservoir to meet power demand and (ii) inability of the reservoir to meet irrigation demand, are considered for illustration of multiple failure events of different types. This scenario illustrates the combination of both, the structural and functional failures for multiple consecutive events. The variation of dynamic resilience for different types of consecutive failure events is shown in Figure 11. Figure 11a shows the dynamic power resilience. Due to multiple failure events, the power resilience drops three times, at day 361, 500, and 1387, respectively. The first and the third drop in the power resilience curve (Figure 11a) are because of functional failures (corresponding to periods of high demand and insufficient supply). The system is able to provide some partial releases during these two failure events and hence the power resilience does not drop to zero. This shows the robustness of the system to a functional failure caused by lower inflow and high demand. The robustness values for power production are 0.17 and 0.06 for these two disturbance events. The second drop in the power resilience curve is due to the turbine disturbance event introduced at day 500. It is observed that the system recovery from failure due to inability to meet the demand (functional failure) is faster than the recovery from turbine disturbance (structural failure). The first failure due to high demand is 10 days long and the second lasts 86 days, whereas the turbine disturbance is 200 days long. Also, the failure of not meeting the demand is not a complete failure since partial release allows the system to operate with reduced level of performance. Figure 11b shows the dynamic irrigation resilience. There are two drops in irrigation resilience due to the high demand for water. Figure 11c shows the dynamic resilience of the reservoir system, which is the combination of power and irrigation resilience obtained using equation (15). After
the three failure events, the power, irrigation, and reservoir performance attains steady state at day 1787, 1821, and 1804, respectively. The values of power rapidity, irrigation rapidity, and reservoir rapidity are 311, 345, and 328 days, respectively. The comparison of traditional measures and the dynamic resilience for the consecutive disturbance events of different types is given in Table 4. The values of dynamic resilience for each system component (power, irrigation, and reservoir) extracted from Figure 11 at day 1700 are also given in Table 4. If we analyze the traditional measures, it is observed that the reliability of the reservoir system is slightly higher than in the Scenario 3, since the total duration of the failure events is shorter. This is the only scenario where the traditional measures are able to capture the impact of different failure types on the overall reservoir performance. Looking at the dynamic resilience measure, it is found that the resourcefulness of reservoir system is higher compared to the resourcefulness of individual components. Integrating the individual components of the system results in the increase of the reservoir resourcefulness. In this case, the dynamic resilience measure is exhibiting another advantage as compared to the traditional resilience—ability to clearly capture and describe the reservoir system response to multiple failures of different nature. Having ability to obtain the resilience value for any time $t$ can be of high practical value for the reservoir managers in the process of preventive maintenance and emergency response by indicating where, when and how different response at different time may affect overall reservoir resilience.

4.5. Discussion

Detailed understanding of dynamic system resilience can point to some potential measures that can increase the Koyna reservoir resilience. For example, having in stock necessary mechanical and electrical components may shorten the breakout time (in our case 200 days) and speed up the system recovery through the effective mobilization of resources (shortening the recovery time and changing the slope of the recovery part of the resilience curve—resourcefulness). Another potential option could be to increase the maintenance level which can result in the increase of Koyna reservoir robustness by preventing loss of complete power production. In a similar way, many other proactive and reactive measures can be analyzed using presented reservoir system resilience method in order to prevent or minimize the impacts of future reservoir disturbances and increase the reservoir resilience.

For all four scenarios, the dynamic resilience of the reservoir system did not reach the predisruption level. This is due to the choice of performance measures used in this study and shown in equations (20) and (21). The model releases are always smaller or equal to the demand depending on the available storage in the reservoir and never exceed the specified demand. Since, the performance measures are formulated as the ratios of actual release to the demand, the value of the ratio is always smaller or equal to one. In addition, the change of system performance becomes constant after the failure event and hence, the system resilience does not reach the predisruption level even though the system reaches the full performance level.

5. Summary

In this study, a new dynamic measure is proposed for quantifying the resilience of a multipurpose reservoir system. The proposed dynamic resilience is based on the adaptive capacity of the reservoir system and the level of system performance. The dynamic behavior of the reservoir system and quantitative resilience is

<table>
<thead>
<tr>
<th>System Component</th>
<th>Reliability</th>
<th>Resilience</th>
<th>Vulnerability (Mm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
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<td>Irrigation</td>
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<td>Reservoir</td>
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<td>0.0129</td>
<td>582.5714</td>
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</table>

<table>
<thead>
<tr>
<th>System Component</th>
<th>Resilience</th>
<th>Robustness</th>
<th>Rapidity</th>
<th>Resourcefulness</th>
</tr>
</thead>
<tbody>
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<tr>
<td>Irrigation</td>
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<td>0.0056</td>
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<tr>
<td>Reservoir</td>
<td>0.73</td>
<td>1.00</td>
<td>224</td>
<td>0.0062</td>
</tr>
</tbody>
</table>

Table 4. Comparison of Koyna Reservoir Performance Using Traditional Measures and Dynamic System Resilience for Multiple Failure Events of Different Types
modeled using system dynamics simulation approach. The variation of dynamic resilience is assessed through the level of system performance for various disturbance events. The adaptive capacity of the multi-purpose reservoir system is expressed through using four aggregated indicators of robustness, redundancy, resourcefulness, and rapidity.

The Koyna reservoir in India is used as a case study, with hydropower production and irrigation water supply as the two main reservoir purposes. The results of the dynamic resilience were compared with the traditional performance measures. The dynamic resilience provides much more detailed insight in the reservoir system performance when compared to the traditional performance measures. The traditional measures result in the same value for various failure scenarios. It is also observed that the characteristics of the reservoir system such as robustness, redundancy, resourcefulness, and rapidity could not be assessed using traditional measures. The dynamic resilience provides clear information of all these system adaptation characteristics that may guide the reservoir planning, design, and operations.

The interactions among the individual system components (in our case reservoir purposes) are captured well by the dynamic resilience, whereas the traditional measures completely ignore them. The presented work leads to a conclusion that the dynamic resilience may be the most suitable measure for assessing the capability of the dams/reservoir systems, where interaction of several individual system components affects the safety of the system.

The dynamic resilience measure can be extended to various spatial applications in water resources systems management. The current research is going on in urban flooding, water supply systems analysis, and interconnected urban network systems resilience to natural disasters. Thus, the dynamic resilience is already proving to be effective and practical measure for real time management of complex systems in response to various disturbances.

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References

