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Jean Carlo Salazar, Philippe Weber, Fatiha Nejjari, Didier Theilliol, Ramon Sarrate. MPC Framework for System Reliability Optimization. Editor E Kowalczuk, Zdzislaw. Advances in Intelligent Systems and Computing, 386, Springer International Publishing, pp.161-177, 2015, Advanced and Intelligent Computations in Diagnosis and Control, 10.1007/978-3-319-23180-8_12 . hal-01254658

HAL Id: hal-01254658

<https://hal.science/hal-01254658>

Submitted on 12 Jan 2016

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MPC Framework for System Reliability Optimization

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Abstract. This work presents a general framework taking into account system and components reliability in a Model Predictive Control (MPC) algorithm. The objective is to deal from an availability point of view with a closed-loop system combining a deterministic part related to the system dynamics and a stochastic part related to the system reliability. The main contribution of this work consists in integrating the reliability assessment computed on-line using a Dynamic Bayesian Network (DBN) through the weights of the multiobjective cost function of the MPC algorithm. A comparison between a method based on the components reliability (local approach) and a method focused on the system reliability sensitivity analysis (global approach) is considered. The effectiveness and benefits of the proposed control framework are presented through a Drinking Water Network (DWN) simulation.

Keywords: reliability, model predictive control, dynamic Bayesian network

1 Introduction

To improve the system reliability and minimize operational costs, component health monitoring should be considered in a controlled system [14]. After failure, the control effort can be redistributed among the available actuators to alleviate the work load and the stress factors on equipments with worst conditions avoiding in this manner their break down [2, 3]. For this purpose, an appropriate method should be developed to redistribute this control effort until maintenance actions can be taken. Over-actuated systems implies actuator redundancy, this means that the number of control inputs is larger than the number of inputs necessary to satisfy the control objective. This characteristic

* This work has been funded by the Spanish Ministry of Economy and Competitiveness through the CICYT project SHERECS (ref. DPI2011-26243), and by the European Commission through contract EFFINET (ref. FP7-ICT2011-8-318556).

allows for several combinations of control inputs that produce the same desired output and provide the same system performance [13].

Model Predictive Control (MPC) is an efficient technique to manage actuator redundancy [18]. The MPC algorithm allows to include several criteria in the optimization problem. For example in [10] the authors present an application of MPC to a Drinking Water Network (DWN) taking into account economic, service level and degradation criteria. In [23], MPC formulation includes as a criteria the accumulated actuator usage. Its objective is to maintain the accumulated usage under a safe level at the end of the mission. This approach is exported to several applications, like in [24] where a MPC is applied to a two degree of freedom helicopter and the weighting parameters are used to maintain the degradation of actuators below a safe level.

Reliability is the ability of a system to operate successfully long enough to complete its assigned mission under stated conditions. It can be modelled as an exponential function [7, 30], a Weibull function [3, 12] or a Gamma function [15, 17, 20], among others.

System reliability can be expressed as a stochastic process [22]. For example it is common to use Markov Chains (MC) to model the reliability of components [29]. Unfortunately, in practice the complexity of the system leads to a combinatorial explosion of states resulting in a MC with a very large size.

The use of Bayesian Networks (BN) as a modelling method for reliability computing, taking into account observations (evidences) about the state of the components, has been recently considered in some works [1, 3, 24, 26, 27].

The application of BNs to reliability started at the end of 90's. In [25] the authors present the advantages of BNs in comparison with reliability block diagrams (RBD). In [5] the authors propose to model a fault tree using a BN. A comparison between MC and Dynamic Bayesian Networks (DBN) application to reliability is presented in [28]. In this work a BN is used to model the global system reliability. DBNs are interesting because they allow to model the system reliability with a factorization of the MC states leading to a compact model.

The main objective of this MPC framework is to preserve the system reliability providing control performance. Two approaches are proposed to achieve the goal. A local approach, which is focused in the component reliability, and a global approach, that is focused in the system reliability.

From an availability point of view, the objective is to deal with a closed-loop system combining a deterministic part related to the system dynamics and a stochastic part related to the actuators and system reliability. The effectiveness and benefits of the proposed control framework are shown by its application on a drinking water network.

The rest of the work is organized as follows: Section 2 deals with reliability and its modelling using a DBN. Section 3 describes the formulation used in the MPC problem. Section 4 presents the case study, and the proposed MPC formulation with reliability integration is given. In Section 5 some results of the control application are discussed. Finally, in Section 6 some conclusions are provided.

2 Reliability Modelling

2.1 Bayesian Network framework

Basically, BNs compute the probability distribution in a set of variables according to the prior knowledge of some variables and the observation of others [11]. For instance, let \mathbf{A} and \mathbf{B} be two nodes with two possible states (\mathbf{S}_1 and \mathbf{S}_2) as is shown in Fig. 1. A probability is associated to each state of the node and this probability is defined *a priori* for a root node and computed by inference for the others. The *a priori* probabilities of node \mathbf{A} are $P(\mathbf{A}=\mathbf{S}_{A1})$ and $P(\mathbf{A}=\mathbf{S}_{A2})$.

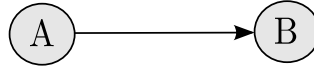


Fig. 1. Basic Bayesian Network.

A Conditional Probability Table (CPT) is associated to node \mathbf{B} and defines the probability $P(\mathbf{B}|\mathbf{A})$ of each state of \mathbf{B} given the states of \mathbf{A} . Thus, the BN inference computes the marginal distribution $P(\mathbf{B}=\mathbf{S}_{B1})$:

$$\begin{aligned} P(\mathbf{B} = \mathbf{S}_{B1}) = & P(\mathbf{B} = \mathbf{S}_{B1}|\mathbf{A} = \mathbf{S}_{A1})P(\mathbf{A} = \mathbf{S}_{A1}) \\ & + P(\mathbf{B} = \mathbf{S}_{B1}|\mathbf{A} = \mathbf{S}_{A2})P(\mathbf{A} = \mathbf{S}_{A2}) \end{aligned} \quad (1)$$

It is possible then to compute the probability distribution for each variable conditioned by the values of the other variables in the graph.

2.2 System reliability

System reliability can be computed from its components reliability through a BN. For this purpose it is necessary to identify all the minimal success paths present in the system.

A minimal success path is a minimum set of components whose functioning (i.e. being up) ensures that the system is up (if all elements of the minimal success path are "Up" then the system is up). The minimal success path cannot be reduced.

For example, consider the system reliability block diagram shown in Fig. 2a, it is composed by three components and it is clear that with a minimum of two components (i.e. components 1 and 3 or components 2 and 3) it can perform its function satisfactorily.

With the minimal success paths identified, it is possible then to build the BN of the system. Fig. 2b shows the BN that corresponds to the three components example. The components reliabilities are represented by nodes e_i . Those nodes are connected to their corresponding minimal success paths represented by nodes P_i . Finally, the system state (*Up*, *Down*) is represented by the binary random variable S [27].

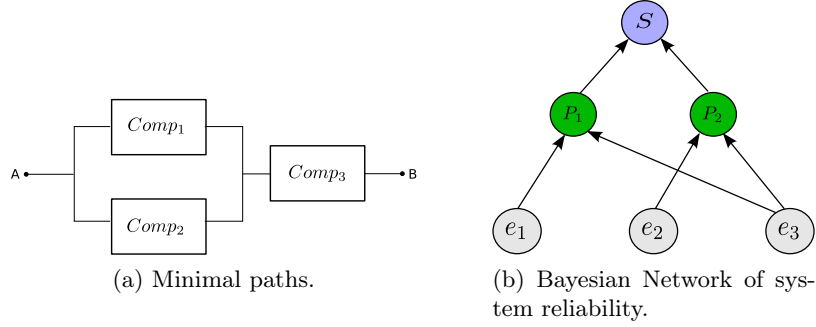


Fig. 2. Three components system example.

Table 1 shows the CPT of node P_1 . It depends on the states of the components e_1 and e_3 and its behaviour corresponds to an AND gate, i.e. all the components in a success path should be available for the system to be available.

The CPT of node S is also shown in Table 2. It depends on the state of success path nodes P_1 and P_2 and has the behaviour of an OR gate, i.e. if there is at least one success path available, then the system will be available. Consequently, the reliability of the system is expressed as:

$$R_s = P(S = Up) \quad (2)$$

Table 1. CPT for node P_1 .

		P_1	
e_1	e_3	Up	Dn
Up	Up	1	0
Up	Dn	0	1
Dn	Up	0	1
Dn	Dn	0	1

Table 2. CPT for node S .

		S	
P_2	P_3	Up	Dn
Up	Up	1	0
Up	Dn	1	0
Dn	Up	1	0
Dn	Dn	0	1

2.3 Importance factors

In order to take into account the global reliability of the system, the use of an importance factor is proposed. Importance factors are criteria used as an evaluation of the components impact over the system. One of them involves determining the system reliability sensitivity against changes in the reliability of the i th component, also known as the Marginal Importance Factor (MIF) [4]. The sensitivity can be computed using the DBN [2, 3], as:

$$\text{MIF}_i = \frac{\partial R_s}{\partial R_i} = P(S = Up|e_i = Up) - P(S = Up|e_i = Dn) \quad (3)$$

where R_s is the system reliability, R_i is the component reliability.

The Diagnostic Importance Factor (DIF) [8] can also be used. This factor represents the probability that the functioning of component i contributes to the functioning of the system provided that the system is not faulty. DIF can be computed using the DBN [2, 3], as:

$$\text{DIF}_i = P(e_i = Up | S = Up) \quad (4)$$

Thus, if component i has a DIF equal to 1, it means that component i becomes critical for the functioning of the system, and if it fails, the system will fail. DIF _{i} criteria involves that components with more importance in the system structure are relieved to mitigate the system reliability decrease.

2.4 Component Reliability

Several mathematical models have been proposed to define the failure rate of a component [9]. In [6], the failure rate is modelled as:

$$\lambda_i = \lambda_i^0 \times g(\ell, \vartheta) \quad (5)$$

where λ_i^0 represents the baseline failure rate (nominal failure rate) for the i th component and $g(\ell, \vartheta)$ is a load function (independent of time) also known as covariate, that represents the effect of stress on the component failure rate. ℓ represents an image of the load applied and ϑ is a component parameter.

The baseline failure rate can be modelled using a Weibull function [2] as:

$$\lambda_i^0 = \frac{\beta_i(k - \gamma_i)_1^\beta - 1}{\eta_i^{\beta_i}} \quad (6)$$

where β is a shape parameter, γ is a location parameter, and η is a scale parameter. In this work, a constant baseline failure rate λ_i^0 is assumed.

Different definitions of function $g(\ell, \vartheta)$ exists in the literature. However, the exponential form is the most commonly used. In [13, 14] the authors propose a load function based on the root-mean-square of the applied control input (u_i) until the end of the mission (t_M), and an actuator parameter defined from the upper and lower saturation bounds of u_i . This load function is used to distribute the control efforts between the redundant actuators, and the control action is calculated using a reliable state feedback.

In this work, it is assumed that the failure rate is provided by the following equation (7):

$$\lambda_i = \lambda_i^0 g_i(u_i) \quad (7)$$

where $g_i(u_i)$ corresponds to the following normalized control action:

$$g_i(u_i) = \frac{u_i(k) - \underline{u}_i}{\bar{u}_i - \underline{u}_i} \quad (8)$$

where $u_i(k)$ is the control effort at time k , \underline{u}_i and \bar{u}_i are the minimum and maximum control efforts allowed for the i th actuator and represents the amount of load on the actuator. The major actuator load corresponds to $u_i(k) = \bar{u}_i$, which leads to the worst failure rate $\lambda_i = \lambda_i^0$, through (7).

This behaviour can be modelled using a DBN [26] taking advantage of the fact that the knowledge of the distribution probabilities and the CPT allows the computation of the distribution probabilities at time $k + 1$. This computation is conditionally independent of the past given the present k , and can be exploited in an iterative process by using the information of time $k + 1$ to compute the distribution probabilities of time $k + 2$ and so on, as shown in Fig. 3.

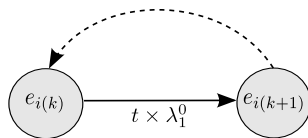


Fig. 3. DBN for component reliability.

Remark that with the inclusion of the amount of load in the failure rate, the DBN models becomes a 1/2 MC [1]. Table 3 shows the discretized CPT for the DBN model with a sample time T_s .

Table 3. CPT for node $e_{i,k+1}$.

		$e_{i,k+1}$	
$e_{i,k}$		Up	Dn
Up	$1 - (\lambda_i^0 T_s g_i(u_i))$	$\lambda_i^0 T_s g_i(u_i)$	
Dn	0		1

Therefore, the component reliability can be expressed as:

$$R_i(k + 1) = P(e_i(k + 1) = \text{Up}) \quad (9)$$

3 Reliability-aware MPC

3.1 MPC formulation

Consider the following linear discrete-time model described in state-space form of an over actuated system with p actuators:

$$\begin{aligned} x(k + 1) &= Ax(k) + Bu(k) + E\varepsilon(k) \\ y(k) &= Cx(k) \end{aligned} \quad (10)$$

where $x(k) \in \mathbb{R}^n$ is the state vector, $u(k) \in \mathbb{R}^p$ is the control input vector with $u(k) \geq 0 \forall k$, $y(k) \in \mathbb{R}^q$ is the measured output vector, $\varepsilon(k) \in \mathbb{R}^m$ is the disturbance vector, $A \in \mathbb{R}^{n \times n}$ is the state matrix, $B \in \mathbb{R}^{q \times p}$ input matrix, $E \in \mathbb{R}^{n \times m}$ is the disturbance matrix, and $C \in \mathbb{R}^{q \times n}$ is the output matrix.

MPC technique is considered to distribute the control effort among the actuators. In this work, the multiobjective optimization problem [21] is formulated as follows:

$$\begin{aligned} \min_{\substack{(\Delta \hat{u}(k|k), \dots, \\ \Delta \hat{u}(k+H_c-1|k))}} J(k) &= \sum_{j=0}^{H_p-1} \sum_{i=1}^q \alpha_i(k) [\hat{y}_i(k+j|k) - y_i^{ref}(k+j|k)]^2 \\ &+ \sum_{j=0}^{H_c-1} \sum_{i=1}^p \Delta \hat{u}_i(k+j|k)^2 + \sum_{j=0}^{H_c-1} \sum_{i=1}^p \rho_i(k) \hat{u}_i(k+j|k)^2 \quad (11) \\ \text{subject to} \quad \underline{u} &\leq \hat{u}(k+j|k) \leq \bar{u} \quad j = 0, \dots, H_c - 1 \\ \underline{x} &\leq \hat{x}(k+i|k) \leq \bar{x} \quad i = 1, \dots, H_p \end{aligned}$$

where \hat{y}_i and y_i^{ref} are the predicted output and the set-point for a H_p horizon respectively, $\alpha_i(k)$ and $\rho_i(k)$ are weighting parameters, \underline{u} and \bar{u} denote the minimum and maximum actuator capacities, and \underline{x} and \bar{x} denote the minimum and maximum state values. The notation $k+i|k$ allows a future time instant $k+i$ to be referred at current time instant k , and the optimization problem consists in minimizing $\Delta \hat{u}_i(k)$ defined as $\hat{u}_i(k) - \hat{u}_i(k-1)$ over a control horizon H_c .

This multiobjective cost function considers three control objectives. The first term of the objective function aims to minimize the tracking error, which is weighted by $\alpha_i(k)$. The second aims a smooth pump operation and the third term penalizes pump operation according to $\rho_i(k)$. For instance, in [21], $\rho_i(k)$ represents the economic cost of pumping, which depends on the variable electric tariffs along a day.

3.2 Enhancing MPC with reliability information

In this work a reliability-aware MPC design approach which aim is to preserve as much as possible the system reliability is proposed. Such an objective is achieved by incorporating in the control design the importance factors seen in Section 2.3 to effectively manage the control inputs in order to reduce the loss of system reliability.

The control inputs managing is performed by the correct choice of the weights in the MPC cost function (11). The weights $\rho_i(k)$ are used then to build the weighting matrix D_u , that distributes the control effort among the actuators, this is:

$$Du_{i,k} = f(\mathbf{\Gamma}_{i:p,k}) := \text{diag}(\rho_1, \rho_2, \dots, \rho_i) \quad (12)$$

where $\mathbf{\Gamma}$ is the criterion by which the control action is distributed among the available actuators. Different definition for $\mathbf{\Gamma}$ criteria are proposed.

The local approach focuses on component reliability $R_i(k)$ provided by the DBN using inference at each time instant. This definition tries to preserve system reliability through preserving components reliability, setting the weights as follows:

$$\rho_i(k) = 1 - R_i(k) \quad (13)$$

With this criteria the aim is to find the optimal control actions and distribute it among the available actuators in a way that actuators with lower reliability level are relieved. Hence, the use of highly reliable components is prioritized.

The local approach assumes an equivalent contribution of component reliability to system reliability. However, this is hardly ever true. In fact, the DBN reliability model can intrinsically explain this relation.

A global approach using MIF criteria is proposed. It is expected that components with a greater contribution to the system reliability are used less with respect to the others. Its aim is to preserve system reliability by setting the weights as follows:

$$\rho_i(k) = \text{MIF}_i(k) \quad (14)$$

Hence, the use of those components with a smaller sensitivity is prioritized. Components with a bigger sensitivity are expected to greatly penalize system reliability, so they are assigned a higher cost.

Another possibility consists in combining MIF and DIF, to take advantage of both as follows:

$$\rho_i(k) = \text{MIF}_i(k) \times \text{DIF}_i(k) \quad (15)$$

This takes into account the sensitivity and critically of the components, i.e. components with less impact in the system reliability and less critical to the system functioning will be charged more.

4 Case study: Drinking Water Network

4.1 DWN description

The proposed MPC framework is applied to a part of a Drinking Water Network (DWN) system (Fig. 4) [27]. A DWN is a network which is composed by sources (water supplies), sinks (water demand sectors) and pipelines that link sources to sinks. It also contains active elements like pumps and valves.

Concerning the DWN reliability study, sources, sinks, tanks and pipelines are considered perfectly reliable whereas active elements are not.

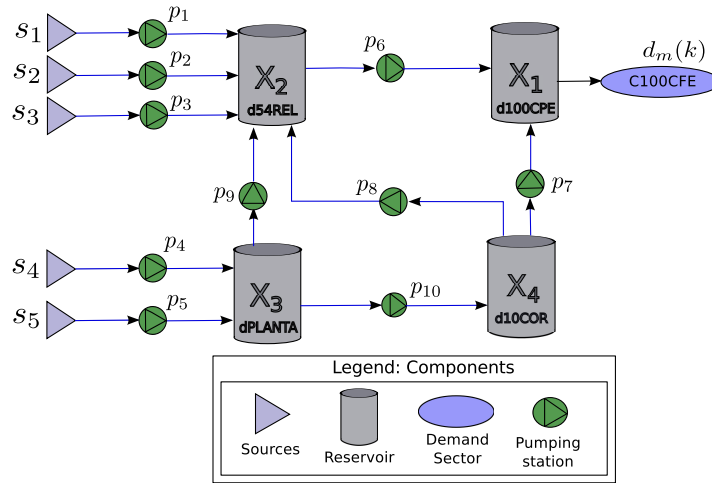


Fig. 4. Drinking water network diagram.

The water demand forecast can be computed using statistical data, in this case it is assumed known and presents a pattern that repeats every 4 days as shows Fig. 5.

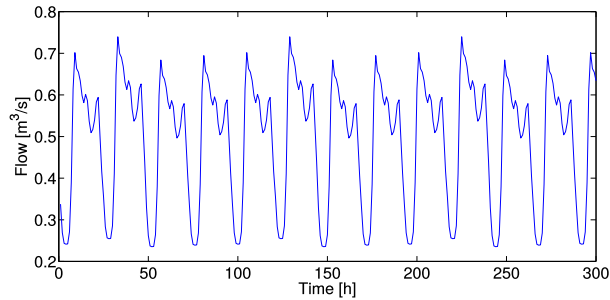


Fig. 5. Water demand.

Remark that, it is assumed that with a single source it is possible to supply the required water demand.

4.2 System reliability using a Dynamic Bayesian Network model

To compute the system and components reliability a DBN is used. The first step before modelling the DBN is to identify all the system components. The system has 10 pumps, 5 sources, 4 tanks and several pipes, Sources, tanks and pipes are considered perfectly reliable and are not subject to loss of reliability. Then, it

is necessary to determine the quantity and composition of each minimal success path. In the case of the DWN system, it has 9 success paths. The availability of each success path depends on the reliability state of its components. So, the second step is to make a list of the components that are involved in each success path (Table 4).

Table 4. Success paths components.

	s_1	s_2	s_3	s_4	s_5	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}
P_1	×					×					×				
P_2		×					×				×				
P_3			×					×			×				
P_4				×					×		×			×	
P_5				×					×			×			×
P_6				×					×		×		×		×
P_7					×					×	×			×	
P_8					×					×		×			×
P_9					×					×	×		×		×

The resulting DBN of the DWN is shown in Fig. 6 where nodes e_i and A_i are drawn for each component (i.e. pump p_i and source s_i , respectively). These nodes are interconnected to their corresponding minimal success path nodes P_i using arcs.

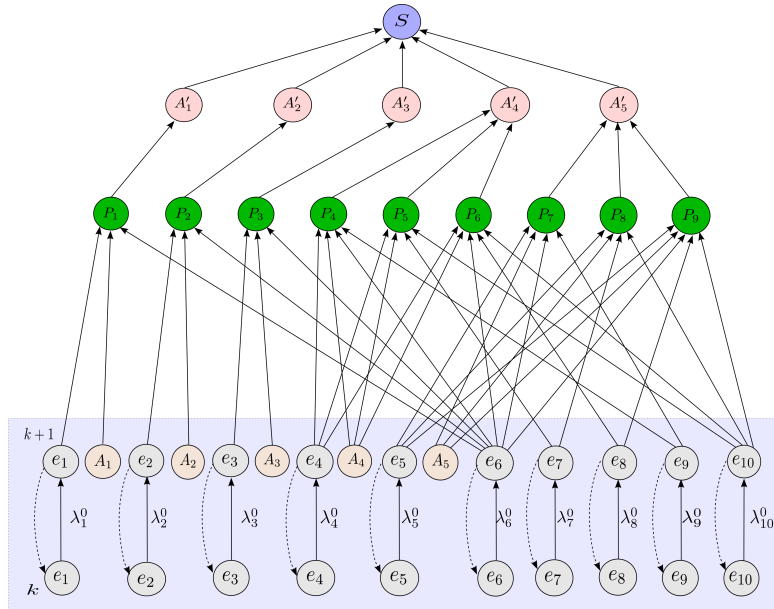


Fig. 6. Bayesian network model of the DWN.

Each minimal success path is linked to the corresponding source availability node A'_i . This layer provides the availability of each source with respect to the availability of their corresponding minimal success paths considering that sources are assumed perfectly reliable, i.e. $P(A_i = Up) = 1$. Finally, the source availability nodes are interconnected to the system reliability node S [27].

Initially, at instant $k = 0$, the pumps and the system are assumed to be fully reliable i.e. their reliability is 1. Then, the probability of each node is computed using its CPT. In the case of minimal success paths nodes (P_i) their CPT follows an AND gate behaviour, the availability nodes (A'_i) CPT behaviour corresponds to an OR gate as well as the behaviour of the system node S . At each sample time, the reliability R_i of each pump is computed according to its failure rate using the λ_i values of Table 5 in a MC (shaded blue layers in Fig. 6) using the BNT toolbox for Matlab [19] and simulated as discussed in Section 2.4.

Table 5. Pumps failure rate values.

Failure rate λ^0 [$hours^{-1} \times 10^{-4}$]									
9.85	10.70	10.50	1.40	0.85	0.80	11.70	0.60	0.74	0.78

The failure rate for each pump is assumed to be known and it could be obtained from statistical data concerning failures that have already occurred.

As the pumps failure rates depend on the control action through (5) then, each time that the control action is reconfigured according to \mathbf{I} their corresponding importance factor is updated.

5 Results

A hierarchical control structure is assumed, where the MPC formulation proposed in Section 3 produces at every sample time a set of set-points for the lower level flow controllers. Figure 5 displays the daily profile of the forecast water demand that has been taken into account. The initial tank volumes have been set to x_0 . Table 6 provides the simulation parameters.

Table 6. Simulation parameters

parameter	value									
H_p / H_c	24 / 8									
T_s / T_M [h]	1 / 2000									
ρ_i	{1, 1 - R_i , MIF $_i$, MIF $_i$ × DIF $_i$ }									
α_i	0									
\bar{u} [m^3/s]	0.75	0.75	0.75	1.20	0.85	1.60	1.70	0.85	1.70	1.60
\underline{u} [m^3/s]	0	0	0	0	0	0	0	0	0	0
\bar{x} [m^3]	65200			3100			14450			11745
\underline{x} [m^3]	25000			2200			5200			3500
x_0 [m^3]	45100			2650			9825			7622

Figures 7 and 8 present the weights evolution under the studied criteria. As expected, under $1 - R_i$ criteria the pumps with a higher failure rate, i.e. 1, 2, 3 and 7 (see Table 5), are greatly penalized in order to decrease their reliability loss (see Fig. 7).

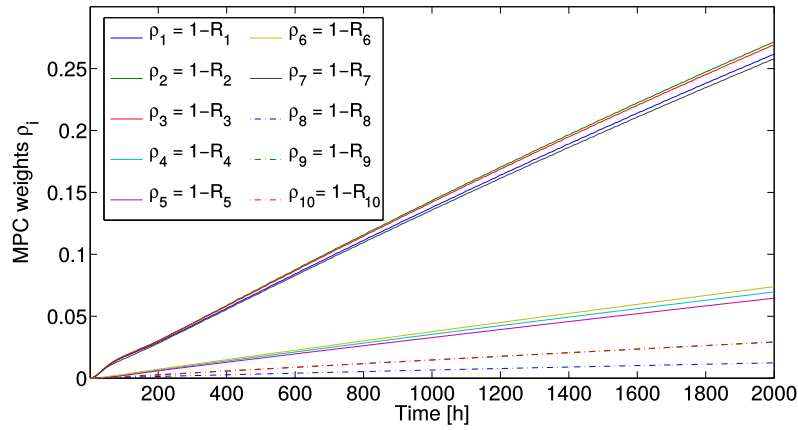


Fig. 7. MPC weights for the case $\rho_i = 1 - R_i$.

Figure 8 shows the MPC weights evolution under MIF_i criteria. It is clear that the weight of pump 6 is bigger than the weights corresponding to the others. This is due to the importance of pump 6 in the operation of the system. In the case of $MIF_i \times DIF_i$ criteria, the weights evolution presents a similar behaviour as in the case of MIF_i .

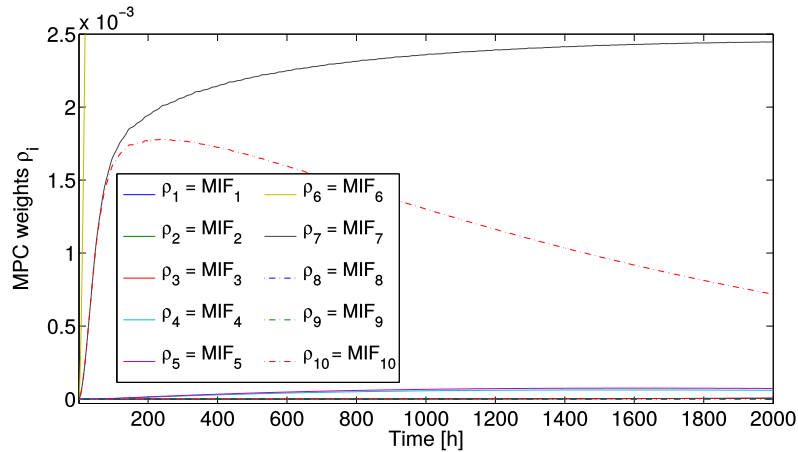


Fig. 8. MPC weights for the case $\rho_i = MIF_i$.

Figure 9 shows the evolution of the pumps control effort corresponding to the scenarios where ρ_i criteria is 1 , $1 - R_i$, MIF_i and $MIF_I \times DIF_i$. Notice that the plots corresponding to MIF_i and $MIF_i \times DIF_i$ are overlapped.

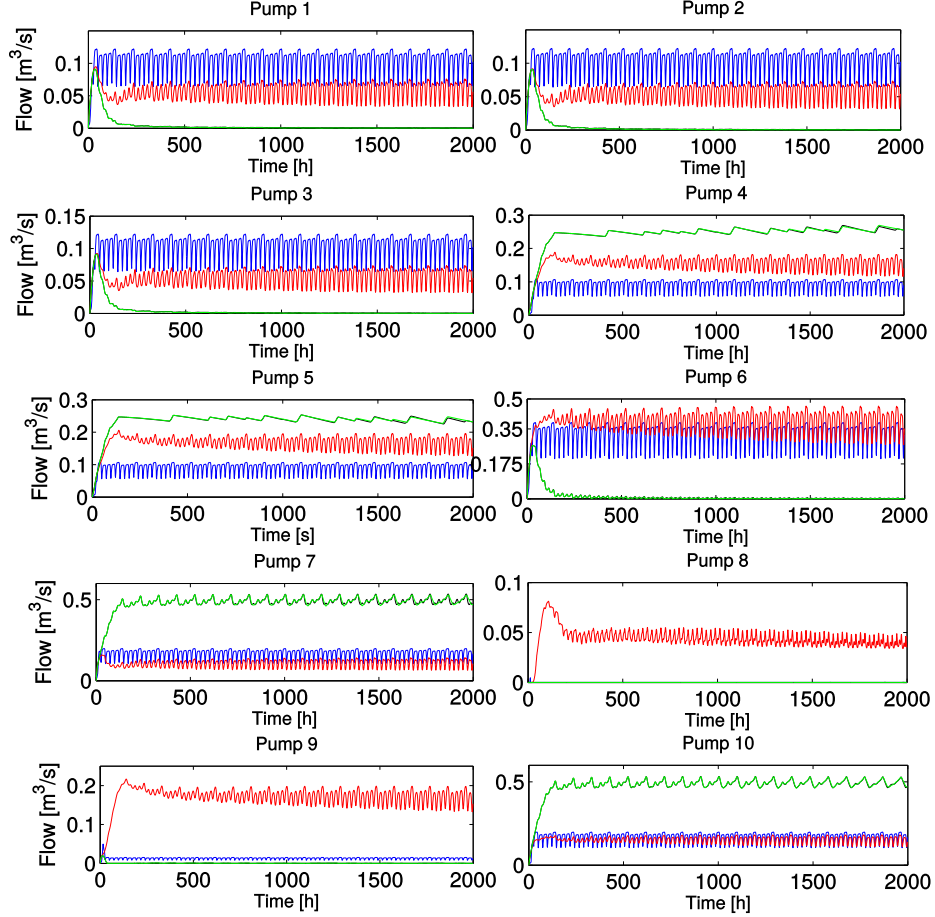


Fig. 9. Pump commands corresponding to $\rho_i = 1$ (blue), $\rho_i = 1 - R_i$ (red), and $\rho_i = MIF$ (black), $\rho_i = MIF \times DIF_i$ (green).

In order to compare the results, the cumulative pump usage U_{cum} index is defined. It is the measure of the pump energy consumption, expressed as:

$$U_{cum} = T_s \sum_{k=0}^{T_M/T_s} [u(k)^T u(k)] \quad (16)$$

The indexes results are presented in Table 7.

Table 7. Results summary.

ρ_i	R_s at T_M	U_{cum}
1	0.97530	1.55685×10^6
$1 - R_i$	0.97903	2.02009×10^6
MIF_i	0.99794	4.20501×10^6
$MIF_i \times DIF_i$	0.99811	4.22680×10^6

Figure 10 shows system reliability (R_s) evolution for scenarios $\rho_i = 1$, $\rho_i = 1 - R_i$, $\rho_i = MIF_i$, and $\rho_i = MIF_i \times DIF_i$.

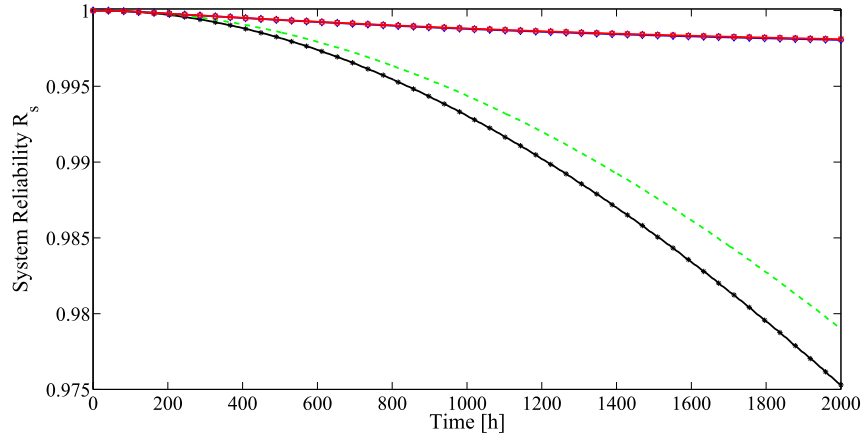


Fig. 10. System reliability: $\rho_i = 1$ (asterisk black line), $\rho_i = 1 - R_i$ (dashed green line), $\rho_i = MIF_i$ (diamond blue line), $\rho_i = MIF_i \times DIF_i$ (circle red line).

For $\rho_i = MIF_i$ the system reliability is improved compared to the other criteria, and a small improvement is obtained using $MIF_i \times DIF_i$. Remark also that an improvement of system reliability in the scenarios MIF_i and $MIF_i \times DIF_i$ involves an increase of the energy consumption in the system. This also occurs in the $1 - R_i$ scenario, where the reliability improvement is not significant. This certifies that, improving system reliability can lead to an increase of energy consumption and the fact that focusing on the reliability of components is not the best strategy to preserve system reliability.

6 Conclusions

An MPC scheme was proposed using the reliability information of the system obtained in real-time from a DBN and tested in a DWN case study. A DBN model of the DWN is used to define the weights of the multiobjective cost function.

Three weights assignments have been proposed. In the first approach, component reliability is targeted, whereas in the second and third approach system reliability is focused using MIF and DIF criteria. It has been shown that focusing on the reliability of components does not guarantee the best system reliability, which was the ultimate goal.

In order to preserve system reliability as much as possible, its sensitivity to component reliability must be preferably accounted for, through MIF and DIF criteria. Analytical computation of this sensitivity is not trivial but a DBN model can provide it easily. The analytical computation needs a model of the system and the DBN offers the possibility to compute it through inference.

In this work the reliability is modelled using an MC. In the case of non-observable degradation it can be modelled using a Hidden Markov Model (HMM) or in the case of exogenous events (i.e. humidity, temperature), those variables can be modelled using Markov Switching Models (MSM) or using Input-Output HMM (IOHMM) [1].

In future research, it could be interesting to consider system availability instead of system reliability. Another issue would involve evaluating system unreliability through other importance factors, such as risk achievement worth and risk reduction worth [16].

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