Maintenance Strategies for Networked Assets ⋆

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Abstract: The purpose of this paper is to analyse the effect of different maintenance strategies for a network of assets whose condition deteriorates progressively along the time. We propose both an agent-based model that considers the dynamics of data traffic and asset deterioration in a data packet transport network; and a network-wide maintenance planning optimisation algorithm. Several network topologies are used to evaluate the maintenance strategies and determine the magnitude of the differences. Simulation results, in networks of different sizes and configurations, suggest that there are cases when a network-wide maintenance strategy could be up to 38% more effective in reducing the impact of the unavailability of assets due to maintenance, while keeping the lowest cost, compared to analysed alternatives.

Keywords: Network maintenance, maintenance optimisation, agent-based maintenance, maintenance strategies, group maintenance

1. INTRODUCTION

Complex industrial systems are built from parts or individual assets that, interconnected, enable the operation of infrastructures, the production of goods or the provision of services. Maintenance activities are key for the long-lasting operation of these systems in line with the expected performance as well as the safety and business requirements. Since the advent of these systems, several maintenance strategies have been devised and implemented, in most of the cases an individual asset's perspective has been adopted.

Although the maintenance strategy might encompass different components, in this paper, strategies are distinguished by implementing one of three well-known maintenance methods: *corrective*, *preventive* and *condition-based* maintenance. The *corrective* maintenance is carried out only after a fault is recognised. Then the failed equipment is repaired or replaced (Paz and Leigh, 1994). The *preventive* maintenance is carried out at regular intervals before equipment failures (Swanson, 2001). In the *condition-based* the physical condition of the equipment is monitored, and the maintenance works can be undertaken based on the *predicted* condition or the *current-state* of the item (Gupta et al., 2012).

Beyond the individual asset perspective, in the last two decades, the group nature of these complex systems has received significant attention. However, as reviewed in section 2, the groups considered are generally simple, context-specific and with a handful of assets. Moreover, it is not clear how the network configuration of the systems of assets can influence the maintenance strategy and in what conditions individual or network-wide strategies can be more advantageous for the system. In this paper we address this gap by: 1) introducing an agent-based model to analyse the performance of individual and network-wide maintenance strategies; 2) proposing a network-wide optimisation algorithm to find optimal maintenance plan for a network of assets whose condition deteriorates with time; and 3) evaluating the model and algorithm using several network configurations.

The remainder of the paper is organised as follows: Section 2 presents the key literature preceding this work. The problem of network maintenance as conceived in this paper is presented in section 3. Section 4 introduces the agent model defining the dynamics of assets and networks for analysis. The network-wide optimisation algorithm is presented in section 5. A case study in the context of digital infrastructures is presented to evaluate the model and algorithm in section 6. The results of the evaluation and analysis are covered in section 7 and finally closing remarks are offered in section 8.

2. GROUP MAINTENANCE AND NETWORK CONFIGURATIONS

Maintenance planning of a group of assets has received significant attention in the last two decades. The most relevant antecedents of this work are those that consider multiple strategies and optimisation approaches.

Different techniques have been employed to find the most effective maintenance strategies. Frangopol and Liu (2007) address safety and cost objectives in a bridge network.

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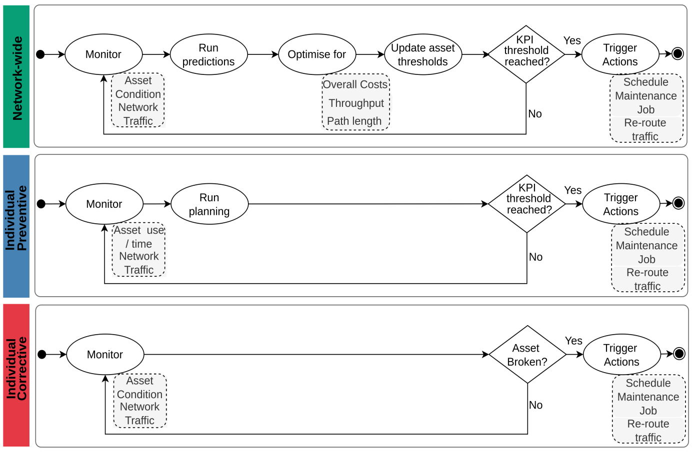

Fig. 1. Control Agent process for each maintenance strategy

They use a two-phase dynamic programming approach, firstly, to reach individual optimal and secondly at network level. Lidén and Joborn (2017) use a mixed integer programming approach to search for plans that optimise long-term railway traffic with regular maintenance periods. Similarly, Meneses and Ferreira (2012) propose a multi-objective decision tool (MODAT) for finding optimal plan of a road network that minimises pavement costs while maintaining quality standards. Li et al. (2014) show the benefits of grouping maintenance are evident when using genetic algorithms to find the optimal maintenance plan for a water distribution.

When the problem is formulated as a Markov Decision Process it can be solved via numerical methods (Liang and Parlikad, 2020), deep reinforcement learning (Zhang and Si, 2020) or multiagent reinforcement learning (Thomas et al., 2021), among others.

As observed in these works, the group maintenance has received more attention in domains related to civil structures and transport and less attention in other infrastructures such as telecommunications. In most of these cases, network topologies are simple, with just a few assets considered in the maintenance group. Likewise, it is difficult to assess the benefit of the group maintenance over other available strategies.

3. NETWORK MAINTENANCE PROBLEM

Given a fixed network topology and the network elements characteristics, the goal of this paper is to analyse and compare the effect of three maintenance strategies: corrective, preventive and network-wide (based on network-wide optimisation algorithm, see section 5). For comparison, the focus is on indicators of quality, specifically the throughput and the overall cost. Cost function per equipment consists of the following components:

$$Cost\ function = t_d * (c_d + c_{lb}) + l_r * c_{ll} + c_p (1)$$

Where factor t_d is *downtime* and l_r is the Remaining Useful Life (RUL) at the start of maintenance. The costs are c_d, c_{lb}, c_{ll} and c_p for *downtime*, *labour*, *loss life* and *parts*, respectively. In the case of preventive maintenance there is no c_d, while corrective maintenance might involve high c_d if maintained equipment is a part of an active traffic flow. The c_{ll} is 0 for corrective maintenance, as it starts only when equipment fails completely, while in preventive maintenance case, this cost depends on how early the maintenance is performed. The shorter the cycle (time between current and previous maintenance), the higher the cost. c_p is fixed per maintenance regarding of the duration and is higher for corrective maintenance. c_{lb} is fixed per time step. The total network maintenance cost is the sum of (1) for all the equipment.

A network-wide optimisation algorithm should go beyond corrective and preventive maintenance strategies and incorporate predictive maintenance to, in addition of a more precise monitoring of the asset condition, identify the trade-off between individual strategies leading to the best maintenance plan with minimum costs and maximum network performance. Moreover, the optimisation algorithm should provide the network-wide traffic re-routing based on the maintenance planning.

4. AGENT-BASED MAINTENANCE PLANNING

4.1 Agent-based Model

To implement and analyse individual and network-wide maintenance strategies, an agent-based simulation model is proposed. This approach is chosen as it allows to configure individual dynamics of each asset and observe the effect on the entire system (network). The networked system subject to maintenance is represented as a multiagent network. There are two types of agents: 1) those that represent Network Elements (assets), for example, switches or routers and 2) a Control Agent that manages the maintenance plan and controls the network operation.

The network elements are responsible for processing data packets along the network. Data packet routing is based on a simplified implementation of the OpenFlow protocol (Open Networking Foundation, 2009). Network elements keep a flow table that indicates how incoming packets are routed to reach their destination. If there are no rules in the local flow table, a network element requests a flow routing rule from the Control Agent.

The condition of the network elements deteriorates along the time. This deterioration brings the need of scheduling maintenance activities for the entire network. Each element follows an individual deterioration profile that can be predicted using different techniques, for example, a linear regression or deep neural networks (Chen et al., 2021).

The Control Agent calculates the paths for routing the data packets and triggers the installation of rules in each element's flow table, according to the calculated paths.

4.2 Network Maintenance Planning & Operation

The Control Agent is in charge of planning maintenance and operating the network following a defined strategy and according to the process presented in Fig. 1. Periodically, this agent collects details of the condition of each network element and determines, according to the strategy, when to perform maintenance. When maintenance is due, the Control Agent recalculates paths and updates flow tables of elements affected by the maintenance plan.

The Control Agent runs common cycles of monitoring asset and network state and performing maintenance. In case of corrective, maintenance activities are triggered once the asset's useful life is exhausted. For the other two strategies, a planning phase precedes the maintenance activities. In the preventive case, this is based on a fixed stable use threshold e.g. 100 time steps.

For network-wide, regular predictions of the asset state and the network traffic demands are made using a linear model for the assets and a normal distribution for the network traffic. This information is then fed into the optimisation model (see section 5) that calculates the maintenance plan. This is translated into dynamic thresholds defining the time to run before maintenance is triggered.

When the maintenance is due, the Control Agent queries for alternative paths excluding the failing elements. If an alternative path is available, it triggers the updates of the flow rules for the affected network elements. Data packets are queued on active network elements until alternative paths are found or packets are discarded after a timeout.

5. NETWORK-WIDE MAINTENANCE STRATEGY

The performance analysis of the maintenance strategies considers the corrective, preventive and an extension of the condition-based strategy: the *network-wide* strategy. This strategy uses an optimisation model to find an optimal plan considering the entire network perspective. As corrective and preventive are widely known, this section focuses on the optimisation model that is the core of the network-wide strategy. The optimisation model is formulated as an integer program, which allows to represent both maintenance scheduling decisions and traffic rerouting using integer variables combined in one model.

5.1 Optimisation model

Telecommunication network is represented here as a network $N = (V, A)$, where V - set of nodes and A - set of arcs. The planning of the network maintenance is considered over time horizon $[0, T]$. Let subset $\bar{V} \subset V$ be a set of nodes that are subject to failure in considered time period $[0, T]$. In addition, p_v^t represents probability of failure of node $v \in \bar{V}$ at time t. Set of services is represented as a set of pairs $\{(k, l)\}$, where k is a source node and l is a destination node. Let d_{kl}^t be traffic demand for service (k, l) at time t.

Decision variables. There are two sets of decision variables which best values need to be determined as a solution to the optimisation problem: binary variables w_v^t showing whether node $v \in \bar{V}$ is undergoing predictive maintenance at time interval $[t-1, t)$ ($w_v^t = 1$) or not ($w_v^t = 0$) and integer variable $x_{k,l,a}^t$ representing the amount of traffic from k to l which flow on arc a at time interval $[t-1, t)$. Variables w_v^t will define which nodes undergo predictive maintenance and at what time, while variables $x_{k,l,a}^t$ describe the best routes for traffic flow.

Constraints. The following constraints on decision variables are introduced in this model:

$$\sum_{a \in out(k)} x_{k,l,a}^t = d_{kl}^t \quad \forall t, \forall (k,l), \tag{1}$$

$$\sum_{a \in in(v)} x_{k,l,a}^t \geq \sum_{a \in out(v)} x_{k,l,a}^t \quad \forall t, \forall (k,l), \forall v \neq k, l, \tag{2}$$

$$\sum_{k,l} x_{k,l,a}^t \leq (1 - w_v^t) M \quad \forall v \in \bar{V}, \forall a \in in(v) \cup out(v), \tag{3}$$

$$\sum_t z_v^t = 1 \quad \forall v \in \bar{V}, \tag{4}$$

$$z_v^t \geq w_v^t - w_v^{t-1} \quad \forall t \geq 1, \quad z_v^0 \geq w_v^0 \quad \forall v \in \bar{V}, \tag{5}$$

$$\left(\sum_t w_v^t - t_v^{pred} \right) I_v^T = 0 \quad \forall v \in \bar{V}, \quad I_v^t = \sum_{s=0}^{t-1} z_v^s, \tag{6}$$

where M is sufficiently large number, $in(v)/out(v)$ is a set of arcs entering/leaving node v, t_v^{pred} is processing time of predictive maintenance job on node $v \in \bar{V}$ and additional binary variables are introduced for simplicity: $z_v^t = 1$ if predictive maintenance on $v \in \bar{V}$ begins at $[t-1, t)$ and $z_v^t = 0$ otherwise.

The amount of traffic leaving destination node is equal to demand, see constraints (1). Flow conservation constraints (2) imply that the amount of traffic of a particular connection leaving a node cannot exceed the amount of traffic entering the same node. Constraints (3) guarantee that flow cannot pass through arcs incident with the node that is shut down for predictive maintenance. Constraints (4) and (5) guarantee maintenance without preemption. To ensure that nodes are shut down for maintenance for the duration equal to the processing time of a maintenance job constraints (6) are introduced.

Objective. The objective function is made up of the costs of predictive and corrective maintenance, lost traffic and length/cost of rerouted paths for traffic:

$$\begin{aligned} J = &\sum_{v \in \bar{V}} \sum_t p_v^t I_v^t C_v^{pred} + \sum_{v \in \bar{V}} \sum_t p_v^t (1 - I_v^t) C_v^{corr} \\ &+ \sum_{v \in \bar{V}} \sum_t p_v^t (1 - I_v^t) \sum_{(k,l)} \sum_{a \in in(v) \cup out(v)} \sum_{s=t}^{t + t_v^{corr}} x_{k,l,a}^s \\ &+ \sum_t \sum_{(k,l)} \sum_{a \in A} w_a x_{k,l,a}^t \longrightarrow \min . \end{aligned} \tag{7}$$

6. CASE STUDY: DIGITAL INFRASTRUCTURE

The analysis of each maintenance strategy is based on scenarios in the context of a nationwide digital infrastructure. This infrastructure is built from networks covering the different regions of the country. A backbone network provides long-distance connectivity while metro-regional and access networks enable connectivity within the cities and regions. Likewise, these networks can be broken down for analysis in smaller sub-networks, some of them have similar characteristics to those of networks generated randomly using the the well-known Barabasi-Albert (BA) and Wattz-Strogaz (WS) models (Herrera et al., 2021).

The infrastructure enables data transport services with different requirements. These services group requirements for the transport of data between two end points. One of these requirements is the throughput, indicating the rate with which data packets are delivered from end to destination. Each node is also an asset that deteriorates and hence requires maintenance.

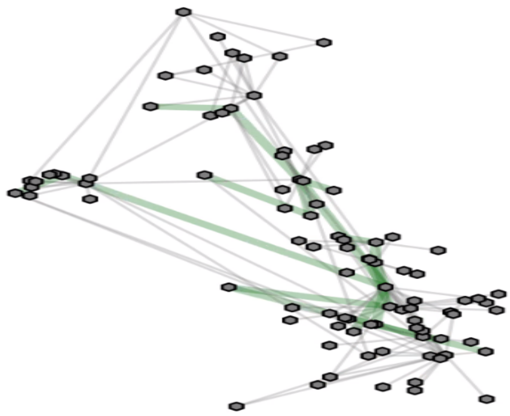

Fig. 2. Backbone network

The analysis of strategies is based on the quality (throughput) and the overall cost. The cost of each strategy is calculated with *downtime, labour, parts and lost life* parameters taking low ($c\_ = 1$) and high ($c\_ = 20$) values, giving a total of 16 configurations. The NAssets.jl[1] Julia library is used for the simulation of networked assets. The network-wide optimisation model is implemented in Python using Gurobi[2] optimisation toolkit. Two scenarios with different networks are set up for analysis.

6.1 Scenario 1: Small Networks

This scenario is intended to observe behaviour of maintenance policies with different topologies and after multiple cycles of deterioration and maintenance. To this end, 20 random networks are generated following the BA and WS models. For each one, random services are also generated such as, combined, the paths required to enable each service, cover 95% of the nodes of each network. Assets follow a linear deterioration function with 40% assets deteriorating faster than the others.

6.2 Scenario 2: Backbone Network

This scenario enables the analysis of the strategies in a large network with many services. The topology used is presented in Fig. 2. The network is based on the UK's metro-core network where spatial location of each node has been synthetically generated.

7. RESULTS & DISCUSSION

In all the figures, the corrective, preventive and network-wide strategies are coloured in red, blue and green respectively. The impact of the asset maintenance in the throughput of a specific service is shown in Fig. 3. When maintenance is required for an asset, that is part of the path that enables the service, the packet flow is broken affecting service throughput. The case shown is the extreme one, when no alternative paths are available, however when backup paths are used, the throughput alterations are minimal. The timing of the maintenance can be observed according to each strategy.

[1] https://github.com/mperhez/NAssets.jl
[2] https://www.gurobi.com/

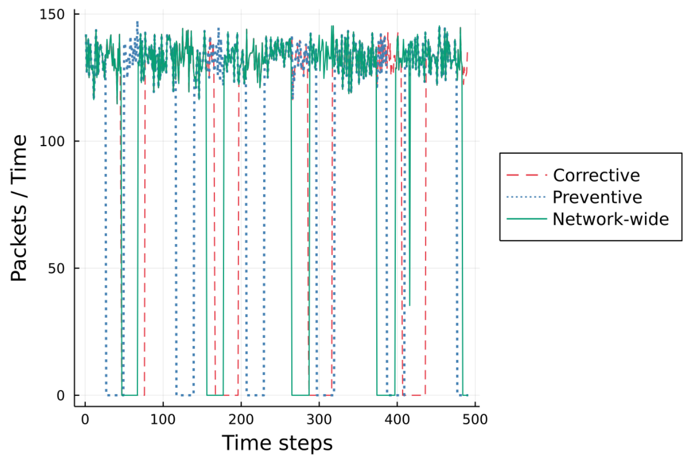

Fig. 3. Impact of Maintenance Operations on Service Throughput.

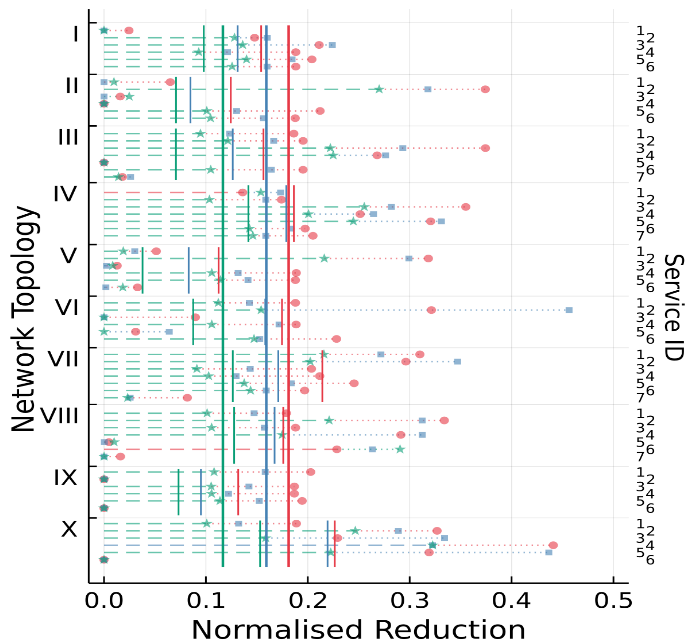

Fig. 4. Throughput Reduction due to maintenance operations for 10 Barabási-Albert networks. Red, blue and green for corrective, preventive and network-wide strategies. Horizontal lines show reduction per service, bottom and top line colours as per strategy causing minimum and maximum values. Vertical lines show individual and overall network mean.

Results for 10 small BA and 10 WS networks are presented in Fig. 4 and Fig. 5, respectively. The plots show that, on average across networks, the highest reductions of throughput are caused by the corrective strategy (0.31 for WS and 0.18 for BA) and the lowest by the network-wide strategy (0.12 for BA and 0.22 for WS), regardless of the topology. In few cases, the network-wide strategy, is not the best for some individual services, see for example, horizontal red lines for networks IV and VIII in Fig. 4, where the corrective is the best for individual services. Note that reduction is higher, on average, in WS networks than in BA networks, this is explained as in BA networks alternative paths are available hence causing minimal or

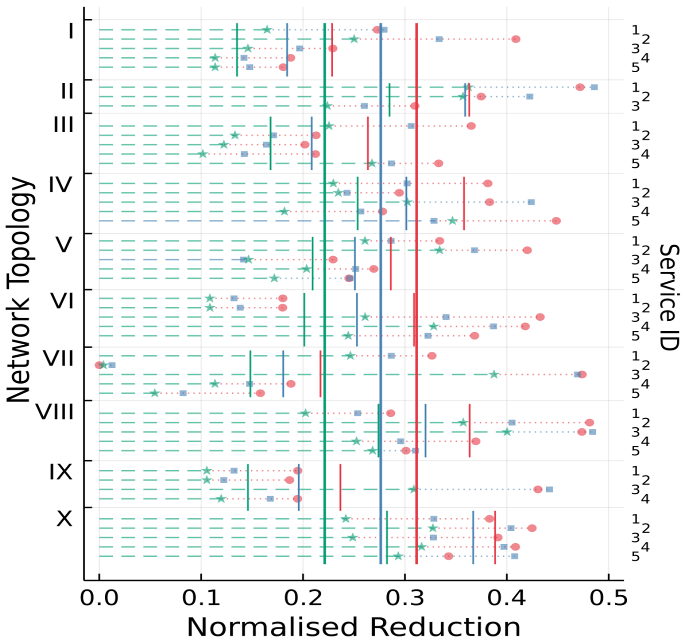

Fig. 5. Throughput Reduction for 10 Watts-Strogatz networks. Red, blue and green for corrective, preventive and network-wide strategies. Horizontal lines show reduction per service, bottom and top line colours as per strategy causing minimum and maximum values. Vertical lines are individual and overall network mean.

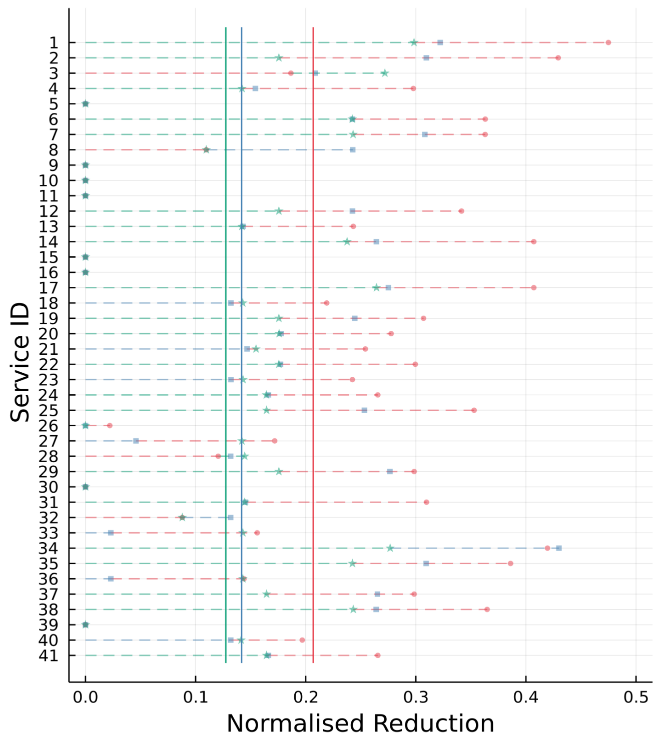

Fig. 6. Throughput Reduction for Backbone Network. Red, blue and green for corrective, preventive and network-wide strategies. Horizontal lines show reduction per service, bottom and top line colours are according to strategy causing minimum and maximum values. Vertical lines show network mean.

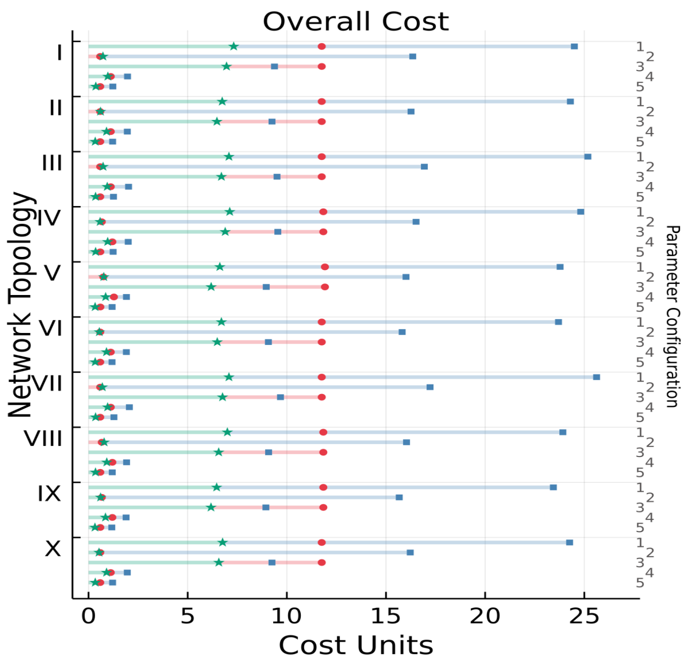

Fig. 7. Maintenance Costs for 10 Barabási-Albert networks and 5 Configuration Parameters. Lines show the distinctive values of 5 configurations of *labour, downtime, parts and lost life* costs. Bottom and top line colours are according to strategy causing minimum and maximum values. Red, blue and green for corrective, preventive and network-wide strategies.

no reduction in several services as it can be observed by the overlapping markers at 0.0. For WS networks, this only happens in one service of the network VII. The network-wide strategy performs between 19.91% and 35.62% better, on average, than the alternatives, with larger differences in the BA networks. The results for the metro-core network scenario in Fig. 6 show the same trend observed in the small network scenario. However, the improvement of the network-wide over other strategies is varied: only 10% better than the preventive, but 38% better than the corrective.

The results for the overall costs, show that in most of the cases, the preventive strategy is the most expensive, as shown by the blue top color of most of the lines in Fig.7 and Fig.8. For the small networks, only 5 distinctive configurations are presented for each network. There are no significant changes due to the network topology. Configurations 1 and 2 correspond to high *lost life* cost parameters, confirming that the preventive strategy is highly sensitive to this parameter in contrast to the other strategies. Configuration 3 shows that the cost of corrective maintenance is higher when all parameters but *lost life* take the highest values. The cost behaviour is similar across small networks and the backbone network.

The network-wide strategy is the one that causes the lowest impact on the quality of the services provided and the most cost-effective, in most of the cases analysed. This analysis discourages the use of an asset's individual preventive strategy for networked assets as costs and impact on quality are higher than the network-wide strategy. When there is tolerance to quality reduction and labour costs are low, the corrective strategy is an acceptable

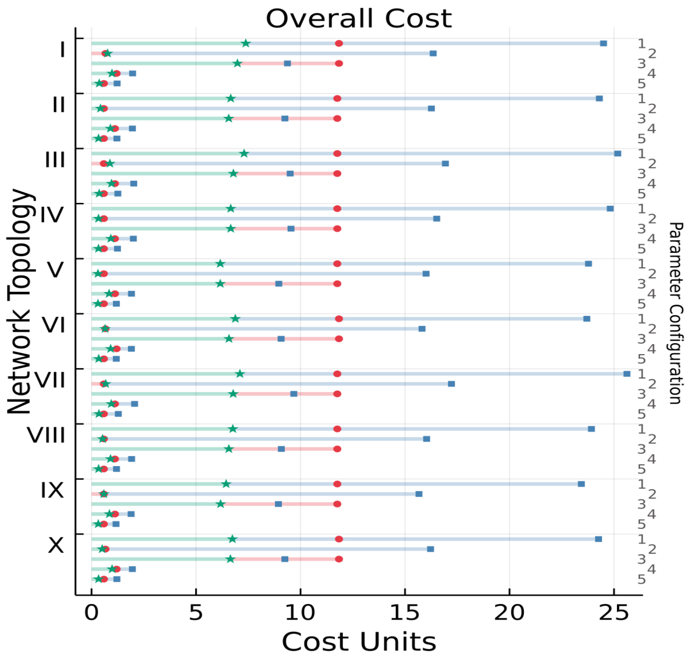

Fig. 8. Maintenance Costs for 10 Watts-Strogatz networks and 5 Configuration Parameters. Lines show the distinctive values of 5 configurations of *labour, downtime, parts and lost life* costs. Bottom and top line colours as per strategy causing minimum and maximum values. Red, blue and green for corrective, preventive and network-wide strategies.

alternative. The corrective strategy is the simplest to implement. On the contrary, as the network-wide strategy considers the state of every asset of the network, it is more computationally demanding for producing the maintenance plan.

8. CONCLUSION AND FUTURE WORK

This paper demonstrated the benefits of a network-wide maintenance strategy across several network configurations. In the cases analysed, this strategy outperforms asset's individual corrective and preventive strategies, achieving between 10% and 38% less throughput reduction than the alternatives. However, the network-wide is the most computing-intensive strategy as it requires entire view of the state of the assets. An individual preventive strategy is discouraged for networked assets when the labour costs are low and there is tolerance to quality reduction, in this case, the overall cost of the maintenance is higher than the benefit obtained compared to other strategies.

In this work, it is assumed that assets are homogeneous with a high, uniform capacity to process data packets. In other scenarios, assets might be heterogeneous and traffic might be distributed among multiple assets when there is no individual asset with enough processing capacity. The current work sets the basis to improve the agent-based and optimisation models and to analyse more complex dynamics in a future study.

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