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Observation scheduling and simulation in a global telescope network

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HIGHLIGHTS

- Simulation framework for a telescope network based on discrete-event system.
- Multi-objective optimization problem: Maximize acceptance and minimize time.
- A new telescope decision algorithm based on a generalized linear regression model.
- Pareto frontier comparative among different decision algorithm.
- The new algorithm shows the best performance.

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ABSTRACT

The GLObal Robotic-telescope Array is an e-infrastructure composed of a network of telescopes with the aim of providing citizen science capabilities. To allow it, the network is managed by a scheduler that receives observation requests from users, and decides the best telescope to execute them. The objective is to maximize the number of accepted observations and minimize the elapsed time between the user request and its execution. This issue arises as a multi-objective optimization problem that can be solved by means of different methods. Therefore, the aim of this work is to develop a new probabilistic algorithm that decides the best telescopes to execute a requested observation, taking into consideration the optimization problem. To perform a comparison of the new algorithm with others, a model of the telescope network has also been created and validated through information obtained from the real network. Finally, a comparative of the new algorithm with previously developed ones has been carried out to demonstrate their performance in the model.

1. Introduction

There are two tendencies in the development of astronomical facilities. The first one is related to the construction of large isolated telescopes to observe faint objects; the second one is the creation of telescope networks to take advantage of different locations of observatories. In that way, telescopes such as The Large Synoptic Survey Telescope (LSST) or the 3-m telescope at the Calar Alto (CAHA) observatory are examples of the first trend. The first one will be an 8-meter telescope, expected to make significant contributions to inventory of the Solar System [1]; meanwhile, the latter has started a survey of M-draft stars in search of terrestrial exoplanets thanks to the use of the CARMENES spectrograph [2]. Regarding the telescope networks, both professional and amateur can be found. The Falcon Telescope Network (FTN) [3] is an educational and research network, where students and teachers learn different astronomical issues such as observation proposal submissions, telescope operations and data analysis. Las Cumbres Observatory Global Telescope Network (LCOGT) [4], the Burst Optical Observer and Transient Exploring System (BOOTES) [5] and the Russian robotic MASTER telescope network [6] are examples of telescope networks for professional astronomers. The first one is made up of 18 telescopes, which always has at least one telescope at night, and it is focused on time-domain astronomy, i.e. observation of objects during a long period of time. The BOOTES network has been created to analyze astrophysical transients and high-energy events. Finally, the MASTER network studies gamma-ray bursts and surveys of the sky to discover uncatalogued objects.

In these networks, users request observations that are managed by a network scheduler. This scheduler can be distributed over the network or centralized. In distributed networks [7], a central node makes the decision of which telescope the request will be sent to. On the other hand, in centralized networks [8], the central node plans and executes all the requests, acting the telescopes as

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mere sequencers: receiving instructions and executing them. Most telescope networks follow a planning scheme based on creating a battery of observations for a given period of time, usually one night. The order of the observations is a optimization problem that can be solved in several ways: genetic algorithm [9], mixed integer linear programming [10], etc. There is another trend that is based on scoring all the observations pending at every stage of the execution. It is performed according to a given metric that normally depends on the restrictions specified in the request [11].

Both kind of astronomical facilities, isolated telescopes and network telescopes, entail a great complexity due to the multiple technical requirements that have to be fulfilled. In addition, these systems have to autonomously work for large period of time, which makes mandatory the analysis of the efficiency and performance of the whole system or part of it. In order to achieve this analysis, simulation tools are commonly used. In the case of isolated telescopes, there are examples related to the simulation of different parts of the telescope: the detector [12], the control system [13], the scheduler [14,15], etc.

In telescope networks, they usually test the behavior of a complete telescope within the network with different purposes. In Giakoumidis et al. [16] the interaction between the network components on different activities, such as surveys, monitoring, etc., is analyzed in order to optimized them. The Cherenkov Telescope Array (CTA) [17] studied the scientific capabilities of different telescope configurations, when a new telescope is included within the network [18]. In the FTN, several simulations were carried out before including an adaptive optics system in one of its telescopes to study its performance [19]. It is also usual to simulate the performance of a network or part of it before using it for a new scientific goal. That is the case of the Falcon Telescope Network when using it to detect, track and characterize space objects. This network is going to make simultaneous observations of the same target from multiples sites. To analyze the optimal use of the network to this purpose, simulations of target observations from single and multiples sites have been carried out [20]. Another example is LCOGT, where it is planed to install spectrographs at up to 6 network observatories to emulate a single, globally-distributed spectrograph. Before installing them, simulations to analyze the precision of this subnetwork have been carried out [21].

In last term of 2014, the GLORIA project [22] was launched with the aim of providing a global telescope network where citizens, in general, could research in astronomy. This network is composed of telescopes, with scheduling capabilities, that are actually working on different scientific fields and dissemination issues. This fact makes the telescope operation time to be shared between the owners and the GLORIA users. As part of this network, a distributed scheduler that is able to coexist and interact with the local ones was implemented and deployed [23]. This scheduler manages all the observation requests made by the users, decides to which telescope the observation will be offered and finally sends the observation to the chosen telescope. A key module within the scheduler is the telescope decision algorithm that is in charge of deciding to which available telescope the observation will be offered. This decision takes into consideration the scheduler objectives: maximize the total number of completed observations and minimize the time between the user request and the availability of the observation image. On this matter, two different algorithms were implemented and deployed sequentially on the network. The first one is based on the weather forecast, and the second one is based on fuzzy logic [24]. These two algorithms do not adapt themselves to changes in the telescope network, i.e. a reduction in the acceptance rate for a particular telescope, the disconnection of any of them due to technical problems in the observatory, etc.

Thus, in order to improve the performance of the GLORIA network, this paper extends previous works proposing a new telescope decision algorithm based on a probabilistic method. This new algorithm is able to adapt its response to changes in the network and consequently, to achieve better results that the ones obtained with the previous algorithms.

To properly compare the proposed method with the previously developed ones, all of them need to be tested under the same conditions. These conditions include weather forecast on the observatory as well as the telescope availability. As these conditions cannot be forced in the real network, a simulation environment has been developed using a discrete-event based model. The main advantage of the simulator, in contrast to the previously described ones, is that it is able to analyze the whole telescope network performance.

First, an overview of the GLORIA network in Section 2 is presented. Then the model of the whole network, detailing each part of it, is in Section 3. Section 4 describes the new probabilistic algorithm able to adapt to changes in the telescope network. Finally, the network model validation and the comparative results of the three algorithms are shown in Section 5, followed by the discussion and conclusions in Sections 6 and 7 respectively.

2. GLORIA overview

The GLORIA network (GLObal Robotic telescope Intelligent Array) is composed by 18 telescopes spread out over four continents in both hemispheres (Fig. 1); including both solar and night telescopes with different optic features. The network is offered to both amateur and professional astronomers, providing the telescopes and the data acquired by them. For professional astronomers the GLORIA network is useful to those who do not have astronomical facilities available. Moreover, the GLORIA network makes possible the access to remote telescopes where astronomers can observe targets that are not visible from their usual location. Regarding amateur astronomers, GLORIA provides the access to professional telescopes to users that generally would not have access to them.

The batch experiment is one of the available features that GLORIA provides, it consists in submitting a observation request to the network. This request is managed by the GLORIA scheduler that decides which of the available telescopes will execute it. The observation request includes all the information required to manage and execute the observation. There is a block of instructions and another one of constraints. The first one contains all the data needed to properly execute the observation: the object to observe, defined as RA-DEC coordinates or object name; the filter to use and the exposure time. On the other hand, the constraint block is divided into time, hard and visibility constraints. The time constraints define when the observation has to be performed, parameters as "Not before date" or "Days from New Moon" are set. Regarding the hard constraints, they narrow down the telescope/observatory that finally execute the observation as these constraints fix parameters such us the camera pixels, the field of view, etc. Finally, the visibility constraints are dynamic parameters that define how the object, in relation to its sky position, has to be observed. Examples of this kind of constraints are the minimum target altitude, the distance to the Moon, etc.

2.1. GlSch: the GLORIA scheduler

An important issue in the GLORIA network, which makes it different from any other one, is that the observation time is shared between the telescope owner and the GLORIA network. Owners usually assign a period of time in which the telescope is available to the GLORIA users. GLORIA network, due to this dual public and private usage, is forced to communicate with the control system of each telescope. As it is not a standard component, the interface and its associated feature may be different for each one. RTS2 [25], ACP [26], etc. are examples of different telescope control system

Fig. 1. GLORIA telescope locations.

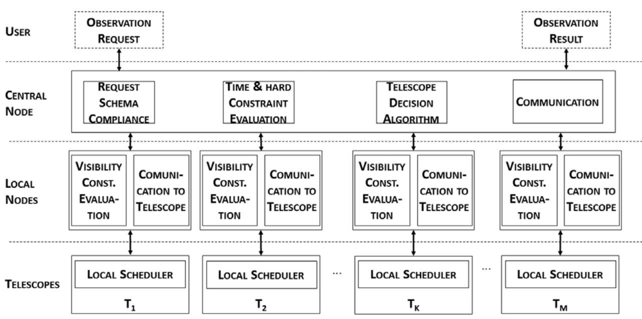


Fig. 2. GLORIA scheduler architecture based on a three layer schema.

among the telescopes in the GLORIA network. This fact makes the telescope scheduler belongs to the GLORIA scheduler architecture, as it will be the one that really executes the observations.

The GLORIA scheduler is based on the three layer architecture depicted in Fig. 2. The upper layer is formed by a unique node, the central node. It is in charge of receiving all the observation requests made by users and making a preliminary analysis of it. This analysis consists in evaluating the time and hard constrains specified in the request. Once this evaluation has been made the central node communicates with the local nodes. These nodes form the middle layer of the architecture and are directly associated to each telescope in the network. Their main function is to perform a visibility analysis to check the visibility constraints in the request. The result of this analysis is sent back to the central node, creating a list of available telescopes with the results of the three constraint analysis. Next, the central node chooses the telescope that will be offered the observation among the ones in that list. To make the decision, a telescope decision algorithm, based on different features is used. Once the telescope has been selected, the central node communicates the decision to the local node of that telescope. This local node establishes a direct communication with the telescope local scheduler to introduce the request into the night plan of the telescope. The local schedulers of the telescopes form the lower layer of the GLORIA scheduler architecture as they are the ones that really execute the observations.

Once the observation has been executed, the acquired target image is available to the user that submitted the request. However, an observation could not be finally executed due to different issues: bad weather, technical problems in the telescope, etc. In this case the central node has to reallocate the observation to another available telescope.

3. Network model

The key module within the GLORIA scheduler is the telescope decision algorithm. Its objective is to choose a telescope that actually executes the observation. Thus, the better decision is made, the better the overall performance of the scheduler will be, as the execution time will be minimized and the total acceptance rate will be increased.

To properly compare different decision algorithms, a model of the GLORIA network is presented next. The parameter to be analyzed in this model is the overall acceptance rate of the network. Thus, the model of the GLORIA network has been made taking into account this consideration.

This acceptance rate depends on several input parameters that are also modeled. They are grouped into three categories: astronomical weather information, target quality and telescope network feedback. The first one provides information of the weather conditions at the observatory locations. It encloses a weather forecast parameter and a astronomical visibility parameter. The target quality information is measured through the target transit altitude, i.e. the maximum altitude that the target can reach at the observatory location; and finally, the telescope network feedback includes the telescope acceptance rate and the user score. The last parameter is an average score that users give to completed observations.

The model of the network can be considered as a discrete-event system, where the reception of an observation request is the event that makes the system evolve from one state to another: from idle state to processing one. And the observation request itself is the system entity that requests a service from the different parts of the system along its way [27]. In order to create the model of different parts of the network, the data produced by the real GLORIA network has been used. These models, coupled with the simulations, have been developed using Matlab-SimEvents.

Below, the network model (Fig. 3), divided into the scheduler and the telescope model, is detailed. Previously, all the input parameters are also modeled.

3.1. Input parameters

To properly run the simulations, several input parameters have to be included and modeled. As it was detailed at the beginning of the section, three type of parameters are used. Their models are explained next.

The models related to the two astronomical weather data, the *weather forecast* and the *astronomical visibility*, are computed using

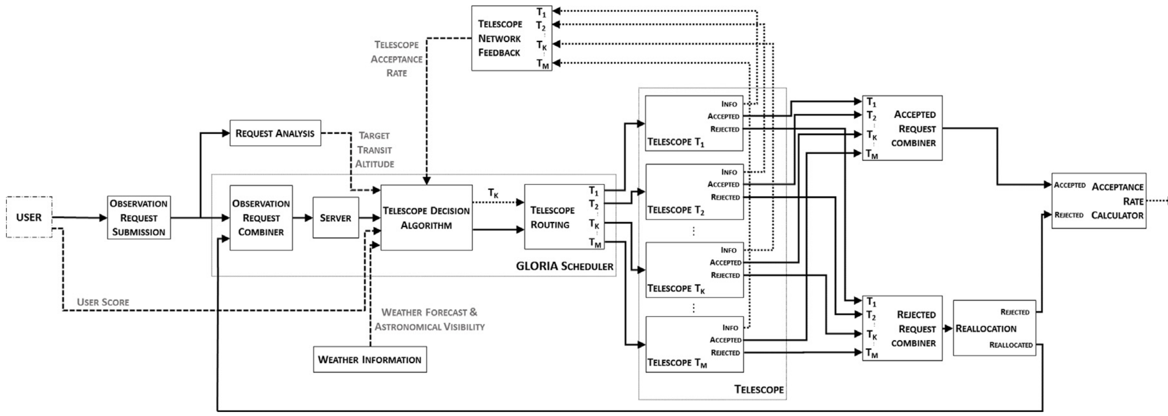


Fig. 3. GLORIA network model divided into three main modules: the scheduler, the telescopes and the inputs. The solid lines represent the path that the observation request follows since it is submitted by the user. The dashed lines symbolize the telescope decision input parameters. Finally, the dotted lines are internal data.

the data directly acquired from the GLORIA network. The weather forecast variable includes information about the cloud cover and the precipitation time. It takes values between 0 and 100; zero value means that the weather is clear with no clouds and no precipitation. As the weather gets worst the value increases. On the other hand, the visibility variable is computed from the seeing data that informs about the astronomical transparency. Its range is also 0–100, the larger this value is, the better transparency condition at the observatory. They have been modeled as a normal distribution applying the central limit theorem. To obtain the different normal distributions the acquired data from the network have been used. These data has been fit to the distribution using maximum likelihood estimation. Fig. 4 shows an example of two astronomical weather models, the ones for the telescopes 2 and 4. It includes the histogram of the weather forecast and the astronomical visibility data (blue bars in the figure) that was acquired during the network operation for these two telescopes. These histograms have been normalized so that it represents an estimation of the probability density function to be better compared with the model. It can be seen as the model (red line) fits the normalized histogram, e.i. the real network data, so it can be properly used.

With regard to the *target transit altitude*, this variable informs about the maximum altitude the target can reach from a specific location. It takes values between 30°–90° , being 30° the minimum acceptable altitude configured in the real GLORIA network. This variable has been modeled through an uniform distribution with limits in these two values. Similarly, the *user score* parameter has been modeled as an uniformly distributed variable with limits between 0 and 10 points.

Finally, the *telescope acceptance rate* is calculated directly from the model while the simulation runs.

3.2. GLORIA scheduler

The GLORIA scheduler has been modeled as a server that receives observation requests and route them to an specific telescope. The best telescope is decided through the telescope decision algorithm that has also been implemented in the model. It has been implemented in a modular way, so that the algorithm could be easily modified in order to test different decision strategies.

Another important point in the model is the definition of the available telescopes per observation request; i.e. the telescopes that fulfill all the constraints specified by the user. They have been modeled through two uniformly distributed random variables: the first one sets the number of available telescopes and the second one specifies the identifier of each of the telescopes in the list. Furthermore, the observation request rate has been included into the model to allow its modification.

Finally, the scheduler model includes the reallocation process. In the real GLORIA network, the reallocation process lasts for three days, i.e. a not executed observation request can be reallocated during a maximum time of three days. Once this period has passed, if the observation has not been executed, the user is informed that no images have been taken. In the GLORIA model, this process has been simplified and the maximum number of telescopes that try to execute the same request has been set to three. It is not exactly the same as in the real GLORIA network, but generally, two consecutive execution attempts are done in consecutive nights.

3.3. Telescope

To analyze how the telescope decision algorithm affects the network acceptance rate, the relevant feature of the telescopes is whether a request will be accepted or not. Thus, each telescope in the network will be modeled as a server that receives entities, i.e. the observation requests, and decides if each request will be executed or not. Although there are different reasons that affect the decision, the most important one is the weather at the observatory location. If the weather is not clear, the telescope control system will keep the dome closed and the offered requests will not be executed. Hence, the acceptance of a request in the telescope model will mainly depend on the weather at its location.

In order to emulate this behavior, a generalized linear regression model has been used. This kind of models establishes a relationship between a response variable and one or more predictors. The response variable is assumed to be a particular distribution within the exponential distribution family [28]. In the particular case of the request acceptance of the telescopes, the response variable is the decision itself, $y \in \{0, 1\}$; thus, the Bernoulli distribution is assumed. On the other hand, as already explained, only the weather at the observatory location is used to predict the behavior of the telescope; so, the model will only use this variable as a predictor. This model is defined by:

$$logit(\mu) = log(\frac{\mu}{1-\mu}) = a + b \cdot \alpha \qquad (1)$$

where μ is the mean response of the model to the given weather forecast, α, at the observatory location; and a and b are the generalized linear regression model parameters that have been estimated. For the specific case of the Bernoulli distribution, that mean response matches the probability of occurrence of a 1 outcome.

To properly fit the model, both the weather at the observatory related to a request and the acceptance or not of it, have been provided by the GLORIA network. The way the network acquires the weather information is through the *7timer* web page, it is a free project that provides the weather forecast for a specified

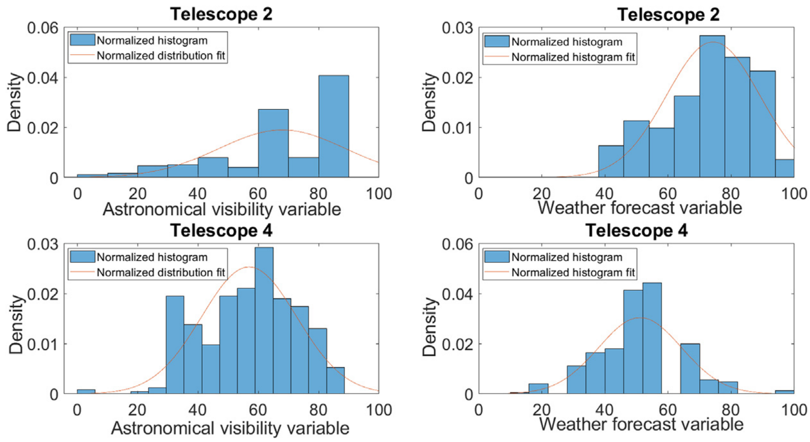


Fig. 4. Comparison between the model and the real network histogram of the astronomical weather variables.

location and it also includes astronomical data, such as the seeing [29]. Based on this information, the GLORIA telescopes compute a weather forecast value that is used in the different telescope decision algorithms that were tested. This value is the one used as a predictor for the generalized linear regression model.

Another issue that has been considered in the telescope model is the average elapsed time between the reception of the observation request and its execution or rejection. This information has been directly obtained from the network logs and it has been computed as the average time among all telescope requests. This average time has been included as a parameter in the SimEvent Server that has been used as part of the telescope model.

4. Probabilistic algorithm

The telescope that will receive the final observation request is a crucial point in the whole scheduling process. A correct decision would minimize the elapsed time between the observation submission and its results, as well as the number of total accepted observations would be maximized. So, this decision can be considered as a multi-objective optimization problem defined by an objective and cost function. On the one hand, the objective function is the maximization of the number of observation requests that are successfully completed; and on the other hand, the cost function is the number of steps during the reallocation process, i.e. the number of telescopes that are offered the observation until one of them finally completes it. The last point is directly related to the elapsed time between the observation submission and the observation execution.

Given a group of observations $\overline{O_N} = \{O_1, O_2, \ldots, O_N\}$ and a maximum number of reallocation steps S, the objective function is defined as:

$$T_a(\overline{O_N}) = \frac{1}{N}\sum_{i=1}^{N} min\left(1, \sum_{A_j^i \in A_S^i} w(O_i, A_j^i)\cdot d(O_i, A_j^i)\right) \quad (2)$$

where $\overline{A}_S^i = \{A_1^i, A_2^i, \ldots, A_S^i\}$ is the list of available telescopes that can execute the observation O_i. $w(O_i, A_j^i) \in \{0, 1\}$ and $d(O_i, A_j^i) \in \{0, 1\}$ are two functions that informs whether the observation O_i could be executed or not by the telescope A_j^i due to weather conditions and telescope availability.

Likewise, the cost function given the same observation group and the same number of reallocation steps can be defined as:

$$M(\overline{O_N}) = \left(1 + \sum_{A_j^i \in A_S^i}(1 - w(O_i, A_j^i)\cdot d(O_i, A_j^i))\right) \quad (3)$$

where $M(\overline{O_N})$ is the worst number of reallocation steps related to that observation group.

The information that is provided by the functions $w(O_i, A_j^i)$ and $d(O_i, A_j^i)$ is only known in the exact moment that the observation O_i is executed by the telescope A_j^i. This fact makes no possible the use of optimization techniques to solve this problem, being the telescope decision algorithm the key module to achieve the best results.

Initially, two algorithms were designed and tested in the GLORIA network. The first one was only based on the weather forecast at the observatory location. However, there are other issues that affect the execution of the observation request, which make considering another kind of algorithm. The aim is to take into consideration additional parameters, in order to prevent the uncertainties that would affect the overall functioning, i.e. image quality, telescope availability, etc. Thus, a fuzzy logic algorithm was designed and implemented for this purpose. However, none of these two algorithms adapted their response to changes in the network along the time, i.e. telescope disconnections or changes in their observation acceptance model. To solve this issue, a probabilistic model is proposed as follows.

The idea is to modify the fuzzy logic algorithm, that achieved good performance results in the GLORIA network, so that it changes its behavior when any of the telescopes changes the way the observations are accepted. The fuzzy logic algorithm uses the five input parameters that were defined and modeled in Section 3. Only two of these parameters are related to external variables that may change the functioning of the telescope. These parameters are the weather forecast (α) and astronomical visibility (β). These parameters will be used to adjust the response of the proposed method.

Instead of directly using these variables as inputs in the fuzzy logic model, the conditional probability (η) of an observation to be accepted per each telescope, given an specific pair of values for the forecast and the astronomical visibility variables, $P(\eta|\alpha, \beta)$, is used. This way, the algorithm will be divided into two parts for each telescope: the prediction of the conditional probability based on information acquired from the network and a fuzzy logic model that finally scores the telescope. All the available telescopes are then scored, finally, the highest punctuation one, Φ_k, is chosen by the decision algorithm using Eq. (4) (Fig. 5).

$$T_k = k|\Phi_k = \max_{1\le i\le n} \Phi_k \quad (4)$$

The prediction of the conditional probability is obtained through a generalized linear regression model. This model establishes a relationship between a response variable and, in this case, two predictors. The response variable is the acceptance or not of a

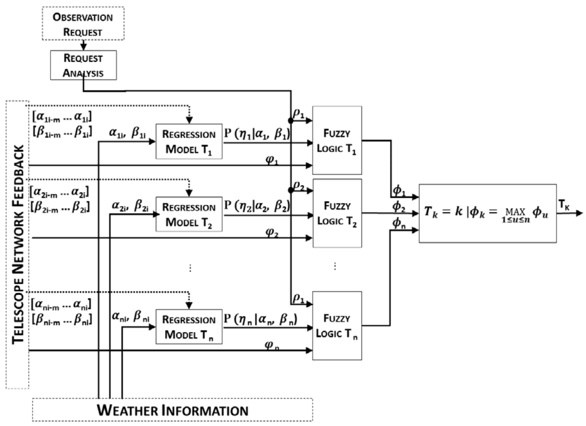


Fig. 5. Schema of the probabilistic decision algorithm.

Table 1
Member functions of the fuzzy model.

	Value	Interval	Type
$P(\eta\|\alpha, \beta)$	Low	0–35	Triangular
	Medium	10–90	Triangular
	High	60–100	Triangular
Target Transit Altitude (ρ)	Low	0–29	Triangular
	Medium	27–67	Trapezoidal
	High	63–100	Trapezoidal
User Score (φ)	Low	0–60	Triangular
	Medium	35–70	Triangular
	High	60–100	Trapezoidal
Telescope Score (ϕ)	Low	0–40	Triangular
	Medium	14–86	Trapezoidal
	High	64–100	Trapezoidal

given observation request, η, and it is assumed to be a Bernoulli distribution as in the case of the telescope models. On the other hand, the bivariable predictor is composed by the weather forecast, α, and the astronomical visibility, β. Thus, this model is defined by:

$$logit(\mu) = log(\frac{\mu}{1-\mu}) = a + b \cdot \alpha + c \cdot \beta \quad (5)$$

where μ is the mean response of the model to the given weather forecast, α and astronomical visibility β; and *a*, *b* and *c* are the model generalized linear regression parameters that have been estimated. That is, μ is directly the conditional probability needed in the probabilistic algorithm $P(\eta|\alpha, \beta) = \mu$.

This model is fitted by the data provided by the continuous simulation of the network, so that it can be adapted to the changes produced in its behavior. The update of the regression model is done through a sliding window technique to make the transitions gradually.

The conditional probability is then used as entry in a fuzzy model which also has the *target transit altitude*, ρ, and the *user score*, φ, as entries. These two last variables were defined in Section 3.1.

The fuzzy model is based on the definition of a set of fuzzy rules that connect the input variables with the output one using qualitative and not quantitative criteria [30]. In Table 1, the different member functions used to properly defined the fuzzy variables are shown.

The rules that govern the functioning of the fuzzy model are defined through *if–then* statements. The '*if*' part sets the input variable criteria, whereas the '*then*' part establishes the value of the output variable according to that criteria. The fuzzy rule that

Table 2
Telescope score.

$P(\eta\|\alpha, \beta)$	ρ	φ	ϕ
Low	–	-	Low
Medium	Low	Low	Low
Medium	High	Medium/high	High
Medium	Low	High	Medium
Medium	Medium/high	Low	Medium
Medium	Low/medium	Medium	Medium
High	–	Medium/high	High
High	Low/medium	Low	Medium
High	High	Low	High

established the behavior of the fuzzy model is define in Eq. (6):

$$\begin{aligned} IF\ P(\eta|\alpha, \beta)\ AND \quad & \rho \\ AND \quad & \varphi \\ THEN \quad & \phi \end{aligned} \quad (6)$$

Table 2 summarizes the telescope score according to the set of fuzzy rules previously defined. It should be noted that the hyphen indicates that the variable can take any of the values within the fuzzy set.

5. Results

This section is focused on two objectives. The first one is the validation of the network model that was explained in Section 3. The second one is the implementation and validation of the proposed probabilistic algorithm, detailed in Section 4, within the model, comparing it with the previously developed fuzzy logic and weather forecast based ones.

5.1. Model validation

The telescope network model has to be validated in order to verify that the simulation results correspond to the real network. The key part is the telescope itself, the accuracy of the acceptance rate will result in a better model. Thus, the first step of the validation process is to test the telescope behavior. To properly make this validation, only the telescope model has been enabled in the simulation, the rest of parameters have been modified to directly use the information acquired from the real GLORIA network. So, the simulation output, in this case the telescope acceptance rate, can be directly compared with the one of the network in the period of time where the data was retrieved.

The period of time used for this validation step was the time the fuzzy logic telescope decision algorithm was used, from November 2014 to October 2015. From this period, the model parameters and the acceptance rate of each telescopes were acquired. The first ones were directly used in the model and the latter was compared with the output data of the simulations to check if the telescope model really fits the real ones. To overcome the possible low amount of data to properly run the simulation, simple random sampling with replacement technique has been used [31]. This technique consists in using the data in a random way, without removing it from the sample space. Although the GLORIA network is composed of 18 telescopes, only 8 of them were configured to be used with the GLORIA scheduler. Due to initial problems and the available time offered by the owners to the GLORIA network, only the data of 4 of them have been used in the network model. The ones with biggest amount of data have been chosen.

Fig. 6 shows the acceptance rate of the telescopes during that period of time couple with the same information but obtained through the simulation of the model. As it can be seen, the results of the simulation are quite similar to those of the real GLORIA network. The maximum difference occurs for the second telescope,

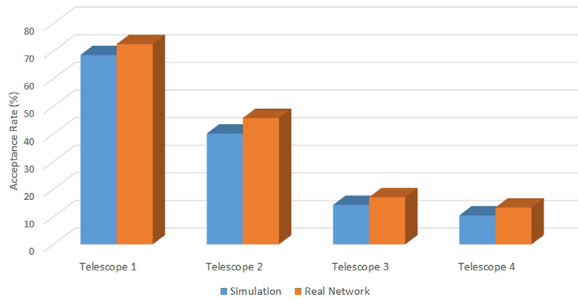


Fig. 6. Comparative between the GLORIA telescope acceptance rate and the one obtained with the model simulation for each individual telescope.

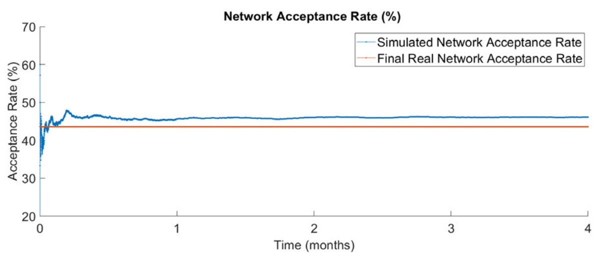


Fig. 7. Comparative between the overall GLORIA acceptance rate and the one obtained with the network model simulation. Both, the real data and the simulated one, have been acquired when the fuzzy logic decision algorithm was used.

being lower than 6 points. The difference is due to the simplification in the model, where only the weather information has been used to decide if the telescope accepts or rejects an observation. Although this decision is really affected by more issues, this simplification produces, as it can be seen, accurate results.

Once the individual telescope model has been validated, the whole network and parameter model were enabled to check if the tendency of the simulated overall acceptance rate of the network matches with the real one. For this purpose, all the models that were detailed in Section 3 were used during the simulation. Moreover, the observation request rate was set to that of the real network. Fig. 7 shows the evolution of the acceptance rate over the whole simulation time in blue. It can be seen an initial transitory period and how the acceptance rate is stabilized. Together with the simulation data, in red, the total acceptance rate of the real network for the period of time when the fuzzy algorithm was used is shown. The graph shows a small difference, smaller than 3 points, between both.

The difference lies in two aspect that are not completely the same in the simulation and in the real network. The first one is that the fuzzy model deployed in the real GLORIA network had been modified a couple of times to adjust its performance; meanwhile during the simulation, only the latest one was used. The second one is the reallocation process, as it was explained in Section 3 there is a small difference between the real and the emulated process. In fact, the emulated one can be more advantageous, which means the simulated acceptance rate is better than the real one.

5.2. Algorithm comparative

This subsection describes the set of simulations that have been carried out to analyze the performance of the three decision algorithms implemented within the GLORIA network. The first step consists in comparing them under the same conditions, that is, each algorithm was tested with exactly the same observation requests and the same observatory condition per request. The use of

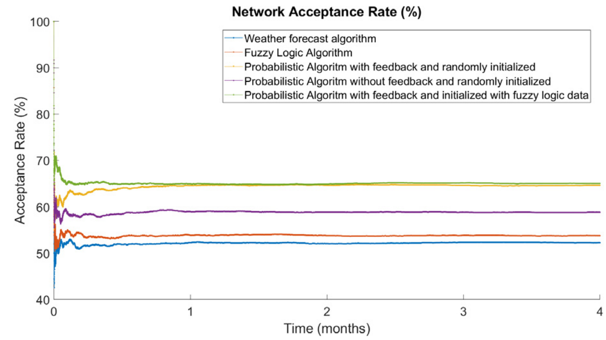
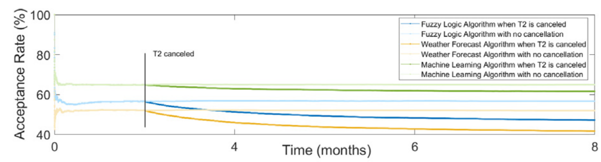
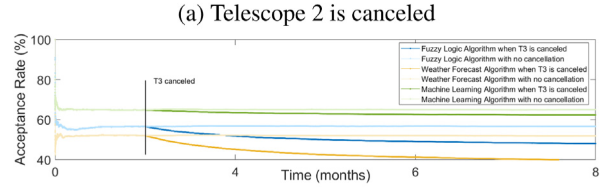


Fig. 8. Comparative among the different telescope decision algorithm under the same simulation conditions.



(a) Telescope 2 is canceled



(b) Telescope 3 is canceled

Fig. 9. Simulation results when one of the telescope network is canceled. Comparative between the total network acceptance rate when no telescope cancellation is produced and when a telescope is canceled.

the same observation requests entail that the list of available telescopes per request is the same for the three different algorithms, as well as, the observation request rate.

The generalized linear regression model of the probabilistic algorithm has to be initialized to make the simulations. Two different type of data has been used to this purpose. On one hand, random data has been produced to initially fit the model; on the other hand, the data produced by the fuzzy logic algorithm simulation has been used to initially fit the model. These two cases has been separately simulated and can be seen in Fig. 8. The green line shows the total acceptance rate of the network when fuzzy logic data is used to initially fit the model; and the yellow line shows the behavior when the linear regression model is randomly initialized. It can be appreciated how the latter tends to the first one. Thanks to the network feedback of the probabilistic algorithm, the total acceptance rate of the network is adapted to the one obtained when the algorithm is initialized with fuzzy logic data. The reason of this behavior is that the telescope performance in these simulations has not been modified, so the model obtained with the data produced by the fuzzy logic algorithm is adapted to the network. If a simulation is run with the random initialized model but with the network feedback disabled (purple line in Fig. 8), the network acceptance rate remains as at the beginning of the simulation.

Fig. 8 also shows the performance, under the same conditions, of the fuzzy logic and the weather algorithm. It can be seen as these two algorithms produce lower acceptance rate than the probabilistic one even when this one is randomly initialized and the network feedback is disabled.

Once the different algorithms have been compared in a static network configuration, their performance is tested under changes in the network. Specifically the tendency of the acceptance rate when these changes occurs is studied. One of the worst possible scenario is produced: the cancellation of a telescope. Fig. 9 shows the behavior of the total network acceptance rate when one of the telescope is canceled. This acceptance rate tendency is compared with the tendency when no changes in the network are produced. Fig. 9.a depicts the performance when the telescope 2 is canceled, meanwhile Fig. 9.b shows the performance when the telescope 3 is the one to be canceled. In both figures the performance of the three algorithms are depicted. It can be seen as at the moment that the telescope is canceled the acceptance rate of the three algorithms start to decrease (dark color lines in the figures) if compared with the acceptance rate when the network is static (light color lines in the figure). This decrease appears because there are requests that are being offered to the newly canceled telescope. Both, because it is the unique telescope that can execute the observation due to the observation constraints or because the decision algorithm is offering the request to it instead of offering to another one available.

Although the three algorithms have the tendency to decrease the total network acceptance rate, the decrease slope of the probabilistic algorithm is smaller than the rest ones. The reason lies in the generalized linear regression model used in the probabilistic algorithm to predict the conditional probability of an observation to be accepted. This model is adapted to changes in the network as it can be seen in Fig. 10. This figure shows how the conditional probability of an observation to be accepted ($P(\eta|\alpha, \beta)$) by the telescope 2, given an specific pair of values for the weather forecast (α) and the astronomical visibility (β) variables, changes along the time. Each surface in the figure belongs to a different model during the adaptation time of the probabilistic algorithm. The upper one shows the prediction of the conditional probability when the telescope is still functioning. This probability increases as the weather forecast value decreases, i.e. as the weather becomes clearer and with no precipitation. And regarding the astronomical visibility variable, it can be seen as there is a smooth improvement of the probability when the seeing increases. The rest of the surfaces shows how the regression model changes when the telescope 2 is canceled. The probability starts to progressively decrease up to become zero (dark blue surface) when the model is totally adapted as it can also be seen in Fig. 11. This figure shows the cancellation of telescope 2 at simulation time $t = 69.5$ days. Since then, the conditional probability starts to decrease taking into account the regression model behavior just explained. It can be observed as there is three decrease steps, each one related with the three adaptation steps of the model. During this process the conditional probability changes to be around 0.35 in average to 0, taking values of 0.18 and 0.05 in average for the two intermediate steps. The initial value of the probability takes this values and not higher due to the model of the weather variables in its location. Fig. 4 shows how the forecast variable for telescope 2 has its mean value around 75 which produces probability values near 0.4 when all telescopes are available as Fig. 10 shows.

Once the three algorithms have been analyzed from the point of view of the total network acceptance rate, the elapsed time between the submission of the observation and its results is studied. This time is directly related to the number of steps of the reallocation process, i.e., the number of telescopes that are offered the observation request up to it is finally executed or canceled by the scheduler due to time out.

Fig. 12 shows the occurrence rate of the observations completed in one, two and three steps produced by the simulation in two cases. On the one hand under static network conditions, i.e. when all the telescopes are available; and on the other hand, when the telescope 2 was canceled. In the first case the observations completed in only one step are higher for the probabilistic algorithm. This algorithm reaches the 73.56% of completed observation

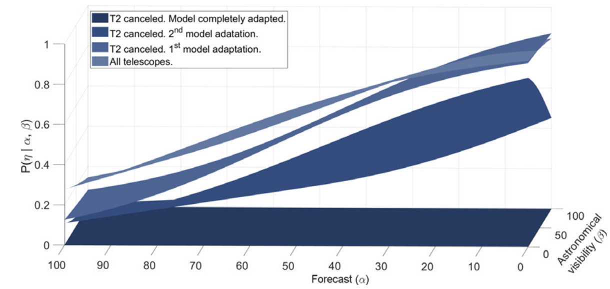


Fig. 10. The adaptation of the regression model of the probabilistic algorithm when telescope 2 is canceled).

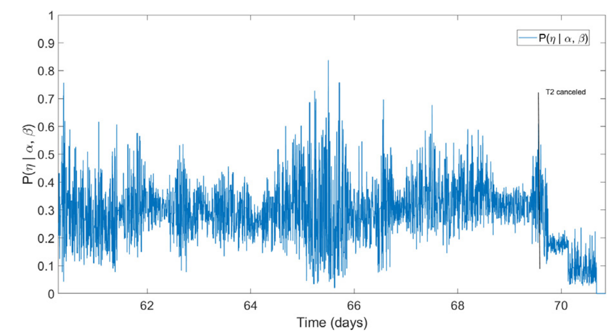


Fig. 11. Instant conditional probability of an observation to be accepted per telescope 2 when it is canceled.

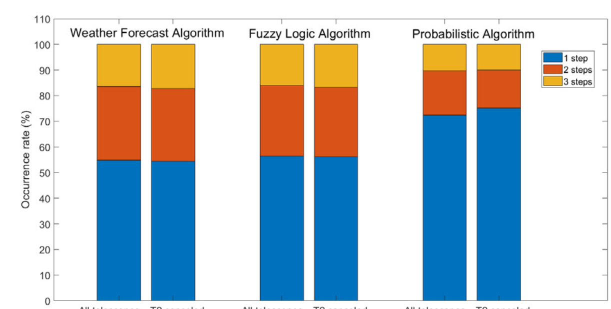


Fig. 12. Reallocation step comparative among the different decision algorithms when telescope 2 is canceled.

request executed by the first offered telescope, meanwhile the weather and the fuzzy logic algorithms stay in a 56.84% and 55.53%, respectively. This fact implies that the overall process time of an observation request is minimized when the probabilistic algorithm is used. Furthermore, if this information is analyzed when the telescope 2 of the network is canceled, as done in the acceptance rate analysis, the results are slightly better. It can be seen as the percentage of completed observation in the first step by the probabilistic algorithm are 3 points higher than the one obtained in static conditions.

Finally, to better compare the algorithms a more detailed analysis has been done. As it was stated in Section 4, the telescope decision problem can be considered as a multi-objective optimization problem defined by an objective and a cost function. This way, the three algorithms are analyzed from the point of view of these two functions. Specifically, Fig. 13 shows the network acceptance rate defined by Eq. (2), versus the maximum number of reallocation steps defined by Eq. (3), for different observation sets of size $N = 100$. In order to better analyze the performance of the different algorithms against the maximum number of steps, the simulations have been configured to have 5 reallocation steps at most.

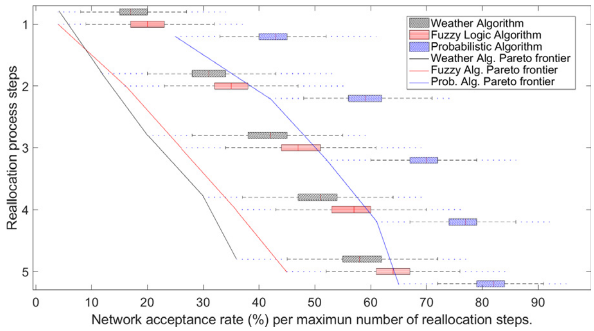


Fig. 13. Pareto frontier for the network acceptance rate versus the maximum number of reallocation steps.

Fig. 13 shows how the network acceptance rate varies depending on the maximum number of reallocation steps. It can be seen as for the same maximum number of reallocation steps, the probabilistic algorithm can reach a higher network acceptance rate. On the other hand, the fuzzy logic and weather forecast algorithms shows a similar performance only when one step is allowed. In the rest of the cases, the fuzzy logic algorithm reaches higher values than the weather forecast one, but always being lower than the probabilistic algorithm. This fact is clearly shown by means of the solid lines shown in the figure. They represent the Pareto frontier for each of the algorithms. The line related to the probabilistic algorithm is the most right-positioned one what points out that the minimum possible network acceptance rate will be higher than for the rest of the cases.

6. Discussion

As seen in the simulation results, the proposed probabilistic algorithm achieves better results than the ones previously implemented in the GLORIA network. This new telescope decision algorithm makes the two objectives of the GLORIA scheduler to be improved. On one hand, the total number of completed observations have increased, both with and without changes in the telescope behavior (Figs. 8 and 9). On the other hand, this algorithm also reduces the time between the user request submission and the request results, stated by a higher number of observations completed by the first offered telescope (Fig. 12).

Moreover, the GLORIA network was configured to have three reallocation steps at most, fact that has been proved to be a good trade-off between the maximization of the completed observation and the minimization of the elapse time to get the observation results. Fig. 13 shows that the increment of the network acceptance rate limits increases in 10 points as the reallocation steps does, up to reach 3 steps. From this number of steps, the increase is lower than 10 points, being the difference minimum for 5 steps (less than 5 points in relation to 4 steps).

Although this probabilistic algorithm could be deployed into the real GLORIA network, as the weather forecast and the fuzzy logic ones were included, the GLORIA project unfortunately finished and it has not be possible to test it in the real network.

7. Conclusion

This paper has described the GLORIA telescope network detailing its scheduler. It is a key module within the network as it decides to which telescope each observation will be offered. Related to this decision, two different algorithms were proposed to try to maximize the total network acceptance rate, as well as, to minimize the elapsed time between the observation submission and its results. The first algorithm was only based on the weather forecast at the telescope location; the second one was based on fuzzy logic using different input parameters. This paper proposes a new probabilistic algorithm based on the prediction of the conditional probability of an observation to be accepted per each telescope.

In order to make a proper comparison among the three algorithms a model of the whole network has been made. This network modeling has been explained in detailed and validated with the data produced by the real GLORIA network. Next, different simulations have been carried out to make the comparison. This study has stated that the probabilistic algorithm produces a better performance of the network both with respect to the total network acceptance rate and the elapsed time between the observation submission and its results.

However, the proposed method does not take into consideration the observation of astronomical events, such as, Gamma Ray Bursts, gravitational waves, neutrinos, etc. As GLORIA project is finished, authors are currently working on the adaptation of the proposed scheduler for the BOOTES telescopes network [5] that is focused on those aspects. In the same way, future works will include new machine learning methods, such as neuronal network, SVM, etc, to be explored and compared with the three ones already studied.

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References

[1] M. Juric, R. Jones, J. Moeyens, et al., LSST data products and tools for solar system science, in: AAS/Division for Planetary Sciences Meeting Abstracts, vol. 49, 2017, 117.09.

[2] A. Quirrenbach, P.J. Amado, J.A. Caballero, et al., CARMENES: an overview six months after first light, in: C.J. Evans, L. Simard, H. Takami (Eds.), Ground-based and Airborne Instrumentation for Astronomy VI, in: Proc. SPIE, vol. 9908, International Society for Optics and Photonics, 2016, p. 990812, http://dx.doi.org/10.1117/12.2231880.

[3] K.C. Gresham, C. Palma, D.E. Polsgrove, et al., Education and outreach using the falcon telescope network, Acta Astronaut. (ISSN: 00945765) 129 (2016) 130–134, http://dx.doi.org/10.1016/j.actaastro.2016.09.006.

[4] N. Volgenau, T. Boroson, Two years of LCOGT operations: the challenges of a global observatory, in: SPIE Astronomical Telescopes+ Instrumentation, International Society for Optics and Photonics, ISBN: 9781510601994, 2016, p. 99101C.

[5] A.J. Castro-Tirado, M. Jelínek, J. Gorosabel, et al., Building the BOOTES world-wide Network of Robotic telescopes, in: Astronomical Society of India Conference Series, vol. 7, 2012, pp. 313–320.

[6] E.S. Gorbovskoy, V.M. Lipunov, V.G. Kornilov, et al., The MASTER-II network of robotic optical telescopes. First results, Astron. Rep. (ISSN: 1063-7729) 57 (4) (2013) 233–286, http://dx.doi.org/10.1134/S1063772913040033.

[7] E. Racero, F. Ocaña, D. Ponz, Towards an autonomous telescope system: the Test-Bed Telescope project, Highlights Span. Astrophys. (2015) 828–833.

[8] E.S. Saunders, S. Lampoudi, T.A. Lister, M. Norbury, Z. Walker, Novel scheduling approaches in the era of multi-telescope networks, in: SPIE Astronomical Telescopes+ Instrumentation, ISBN: 9780819496171, 2014, p. 91490E, http://dx.doi.org/10.1117/12.2056642.

[9] D. Sosnowska, A. Ouadahi, N. Buchschacher, L. Weber, F. Pepe, Using Heuristic Algorithms to Optimize Observing Target Sequences, in: Astronomical Data Analysis Software and Systems XXIII, vol. 485, 2014, p. 73.

[10] M. Solar, P. Michelon, J. Avarias, M. Garces, A scheduling model for astronomy, Astron. Comput. (ISSN: 22131337) 15 (2016) 90–104, http://dx.doi.org/10.1016/j.ascom.2016.02.005.

[11] F. Delgado, M.A. Reuter, The LSST Scheduler from design to construction, in: A.B. Peck, R.L. Seaman, C.R. Benn (Eds.), SPIE Astronomical Telescopes+ Instrumentation, International Society for Optics and Photonics, ISBN: 9781510601994, 2016, p. 991013, http://dx.doi.org/10.1117/12.2233630.
[12] P. Boinee, G. Cabras, A. De Angelis, et al., Gleam: the GLAST large area telescope simulation framework, in: Science with the New Generation of High Energy Gamma-ray Experiments, 2003, p. 141.
[13] X. Shuai, H. Qian, Research of simulation framework for telescope wireless networks control system, in: N.M. Radziwill, G. Chiozzi (Eds.), Software and Cyberinfrastructure for Astronomy II, in: Proc. SPIE, vol. 8451, International Society for Optics and Photonics, 2012, p. 84511Y, http://dx.doi.org/10.1117/12.924504.
[14] A.J. Connolly, G.Z. Angeli, S. Chandrasekharan, et al., An end-to-end simulation framework for the Large Synoptic Survey Telescope, in: G.Z. Angeli, P. Dierickx (Eds.), Society of Photo-Optical Instrumentation Engineers, in: SPIE Conference Series, vol. 9150, International Society for Optics and Photonics, ISBN: 9780819496188, 2014, p. 915014, http://dx.doi.org/10.1117/12.2054953.
[15] S.N. Fraser, I.A. Steele, Observation scheduling simulation framework: design and first results, in: Advanced Software and Control for Astronomy II, in: Proc. SPIE, 7019, International Society for Optics and Photonics, 2008, p. 70190M, http://dx.doi.org/10.1117/12.789369.
[16] N. Giakoumidis, Z. Ioannou, H. Dong, N. Mavridis, Developing a telescope simulator towards a global autonomous robotic telescope network, Publ. Astron. Obs. Belgrade No 92 (2013) 99–104.
[17] C. Bigongiari, C. Consortium, The Cherenkov telescope array, Nucl. Part. Phys. Proc. 279 (2016) 174–181, http://dx.doi.org/10.1016/j.nuclphysbps.2016.10.025.
[18] F. Di Pierro, C. Bigongiari, A. Stamerra, et al., ASTRI Collaboration and the CTA Consortium, Expected performance of the ASTRI mini-array in the framework of the Cherenkov Telescope Array, J. Phys. Conf. Ser. (ISSN: 1742-6588) 718 (5) (2016) 052008, http://dx.doi.org/10.1088/1742-6596/718/5/052008.
[19] M. Cegarra Polo, A. Lambert, Towards a network of small aperture telescopes with adaptive optics correction capability, in: Advanced Maui Optical and Space Surveillance Technologies Conference (AMOS), 2016.
[20] D.A. Hope, A new approach to computing information in measurements of non-resolved space objects by the falcon telescope network, in: Proceedings of the Advanced Maui Optical and Space Surveillance Technologies Conference (AMOS), 2014.
[21] J.D. Eastman, T.M. Brown, J. Hygelund, et al., NRES: the network of robotic Echelle spectrographs, in: S.K. Ramsay, I.S. McLean, H. Takami (Eds.), Ground-based and Airborne Instrumentation for Astronomy V, in: Proc. SPIE, vol. 9147, International Society for Optics and Photonics, 2014, p. 914716, http://dx.doi.org/10.1117/12.2054699.
[22] A.J. Castro-Tirado, F.M. Moreno, C.P. Del Pulgar, et al., The global robotic telescopes intelligent array for e-Science (gloria), in: Revista Mexicana de Astronomia y Astrofisica, in: Serie de Conferencias, vol. 45, ISBN: 5713299503, 2014, pp. 104–109.
[23] M.C. López-Casado, C.J.P. del Pulgar, J. Cabello-Castillo, et al., GISch: A novel scheduler for a heterogeneous telescope network, in: Proceedings of the 30th Annual ACM Symposium on Applied Computing, ISBN: 978-1-4503-3196-8, 2015, pp. 2263–2270, http://dx.doi.org/10.1145/2695664.2695842.
[24] C. López Casado, C.J. Pérez del Pulgar Mancebo, V.F. Muñoz Martínez, A. Castro Tirado, GISch: Planificación de Observaciones en la red de Telescopios GLORIA, Rev. Iberoam. Autom. Inf. Ind. 15 (3) (2018) 339–350, http://dx.doi.org/10.4995/riai.2018.8640.
[25] P. Kubánek, Status, upgrades, and advances of RTS2: the open source astronomical observatory manager, in: SPIE Astronomical Telescopes+ Instrumentation, International Society for Optics and Photonics, ISBN: 9781510602052, 2016, p. 99132U, http://dx.doi.org/10.1117/12.2232555.
[26] R. Denny, A web-remote/robotic/scheduled astronomical data acquisition system, in: Telescopes from Afar Conference, Iberoamericana p. 47.
[27] C.G. Cassandras, S. Lafortune, Introduction to Discrete Event Systems, Springer US, Boston, MA, ISBN: 978-0-387-33332-8, 2008, http://dx.doi.org/10.1007/978-0-387-68612-7.
[28] J. Fox, Applied Regression Analysis and Generalized Linear Models - John Fox - Google Books, 2015.
[29] Q.-Z. Ye, Forecasting cloud cover and atmospheric seeing for astronomical observing: Application and evaluation of the global forecast system, Publ. Astron. Soc. Pac. (ISSN: 00046280) 123 (2011) 113, http://dx.doi.org/10.1086/658201.
[30] E. Trillas, L. Eciolaza, Fuzzy Logic: An Introductory Course for Engineering Students, vol. 320, Springer International Publishing, ISBN: 9783319142029, 2015, p. 204, http://dx.doi.org/10.1007/978-3-319-14203-6.
[31] R. Arnab, Simple Random Sampling, in: Survey Sampling Theory and Applications, Academic Press, ISBN: 978-0-12-811848-1, 2017, pp. 51–88, http://dx.doi.org/10.1016/B978-0-12-811848-1.00003-0.

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