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Extended summary

AN INNOVATIVE APPROACH FOR AUTOMATED JOBSITE WORK PROGRESS ASSESSMENT

Curriculum: Architecture, Buildings and Structures

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Abstract. Construction progress monitoring has always been a major concern for managers. Several are the advantages provided by a reliable approach in this field, among which we cite efficient project performance control and quality control, timely on-site inspections, better control of health and safety prescriptions against job injuries and fatalities, which are still too high. This work addresses the development of a semi-automated approach for construction management, based on two main features: on one side a project management oriented re-organization of project's information based on interoperable BIM (Building Information Modeling) and 4D modeling protocols, which aims to facilitate the control at the execution phase; on the other side a monitoring platform for real-time collection of data, relative to work progress and resources usage, by means of low intrusive technologies. This work also reports on the development of intelligent probabilistic models for real-time estimation of construction progress, which operate on the basis of a continuous data flow collected by monitoring networks deployed on-site. Activity tracks are represented as a set of state variables figuring out workers' effort, equipment and materials usage rates and other knowledge about the context. As estimations are always related to dynamic processes, Dynamic Object Oriented Bayesian Networks have been used to develop a set of first order Hidden Markov Models. Hence, the models are arranged as a sequence of time steps, where each time step propagates evidences collected by the site monitoring sensor network along the time line. The networks have been developed and validated through data collected from a real case, and they have been shown to be able to infer work progress, the accuracy of which depends on the resolution and quality of the collected data.

Keywords. Bayesian networks, Construction management, construction progress, interoperability, real-time monitoring.

1 Problem statement and objectives

Building processes has an information intensive nature that must be properly taken into account in order to avoid information overload: term that has become popular in the last few years for its negative effects. Information overload occurs when the available information exceeds the capabilities of the management system (either human or machine). An efficient management may be hindered by time wasted in information retrieval, by poor structuring and delayed communications [1]. These and other similar evidences led to the birth of a series of research projects on the application of novel IT tools for improved information management and automated control of project performances [2]. The latter being a tough goal, due to the intrinsic difficulties in the wished automated estimation of the various project performance indicators, regarding cost, schedule, labour productivity, materials procurement etc...

The basic idea is that collecting low level field data (e.g. locations of workers, materials and facilities) in real-time and inputting them into interpretation algorithms, progress control and deviation analysis can be inferred with no human involvement. Past experiments demonstrated that workers' tracking and comparison with the project's baseline can be used to assess the activities in progress, and related preliminary prototypes provided an accuracy error lower than 20% [2]. Extending the concept towards automated activity progress monitoring, successful findings have been reported in the field of earthmoving control [3], supply management [4], road construction [5]. Several papers in literature maintain the higher the work standardization the less complex applying automated procedures.

The whole approach requires to develop new technologies and intelligent procedures. Technologies should act as data acquisition systems for tracking and sensing (e.g. movements and vibrations sensors etc..). Algorithms should be able to interpret how the site is evolving and reliably compare it with the project's baseline, in order to progressively update the actual performance indicators.

In its first part this work describes first a possible framework, based on BIM modeling, that may be adopted to organize information at the design phase, such that next progress evaluation is facilitated. Then a first prototype of a platform providing resources tracking and automated production of daily site reports (DSR) is described.

In its second part this work explores a solution to the problem of work progress estimation starting from data collected on site.

Among the outstanding benefits that would derive from automated on-site workers, equipment and material tracking, real-time work progress estimation is considered as one of the most critical. Most of the ongoing research on this field, which is summarized in the next paragraph, is targeted to the following three main goals:

• setting up a cost-effective construction project management, featuring real-time deployment of information, including material and equipment inventory and their traceability;

• performing intelligent waste management, which makes its delivery to the appropriate facility for reuse, recycling, recovery or disposal feasible;

• providing a safe working environments to employees, whose translation into practical situations may be in the form of automated control of proper wearing of safety gears, signaling hazards in real-time, automated predictive collision detection and fall hazards warning in crowded site's areas, and so on depending on the particular kind of work to be performed.

The main focus of this concerns a methodology, based on the use of advanced probabilistic models (Bayesian Networks) and real-time and low-invasive monitoring networks, to automatically estimate the work progress at the execution phase. In particular, the construction of a shopping mall made up of a precast concrete technology has been considered, and the feasibility of a monitoring approach for work progress estimation and based on the automated detection of those resources present on site has been shown.

Moreover, this research step is part of a wider approach aiming at the development of an integrated framework[6] for advanced construction management. Effective monitoring is conditioned upon embedding non-invasive sensors within resources which are expected to operate on-site. To this aim, BIM-based engineering design constitutes a fundamental sup-port, because it allows the disaggregation of any building's design into its elements and phases. In the proposed example a kind of tasks list has been preliminary arranged through BIM, making the assignment of one or more sensor kit to each phase of the construction plan easier and faster (Fig. 1). Once resources and relevant variables are tracked, data collected can be filtered and processed in real-time by advanced probabilistic models, in order to infer the work progress, so that higher reliability and efficiency in Project Control reporting (e.g. Daily Site Reports) and quality inspection management can be achieved.

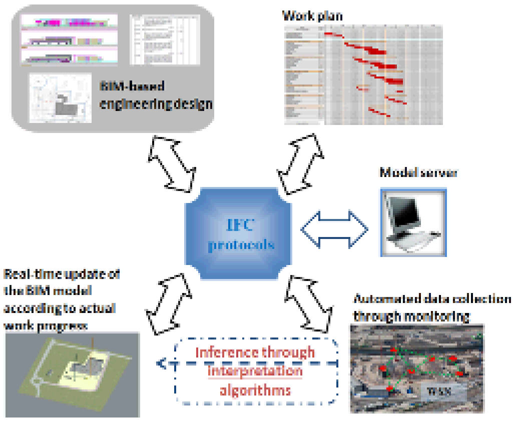


Figure 1-1 Interoperability for work progress management.

On-site tracking is seen as much challenging as promising, thanks to the many advantages that would be brought into the construction process[7]: material management and inventory traceability, automated waste management (i.e. automatic recognition of the waste destination and its cycle), safety support through real-time laborers' warning in case of imminent and probable risk occurrence (e.g. collision avoidance, fall from heights etc…). Assisted design can help avert accidents at the design phase [8], but a real-time warning system is anyway useful to avoid unexpected or difficult to model occurrences [9][10].

Automated progress monitoring would reduce the burden of work usually required to produce project reports editing [11][12], and would make easier communication through automated visualization of construction data [13]. Information awareness is an undisputable excellent tool to manage machines, as it can record operators and operational times in a central server, planning and ensuring inspection and maintenance. However, general economic efficiency is conditioned upon the development of a system for automated project performance control, where indirect data would be intelligently converted into performance measurements [14]. The availability of such an approach would pave the way to many innovations, and sever-al contributions in literature stressed those ones related to quality management: automated remote inspection of infrastructures [15]; control of the construction quality of details that are no more visible after the task is accomplished (e.g. to validate the depth of foundation piers) [16]; tracking and under-standing the context for automated relevant information retrieval during site inspection [17].

This work contributes to the use of advanced probabilistic models (namely Dynamic Bayesian Networks) to perform inference from real-time collected data about the estimation of on-site work progress.

2 Research planning and activities

This 3-years work has been divided in two parts.

In the first part has been developed and tested the wireless localization system used for data gathering in a construction site; also an integration with BIM has been studied for data usage and analisys.

In the second part Bayesian Networks has been focused as a possible solution for automated work progress estimation starting from data gathered. This second subsystem has tested not linked with the localization one, therefore an integration can be done as a part of future works.

The proposed procedure developed in the first part makes such a process semi-automatic in the sense that only a small portion of data collection asks for the involvement of human operators. In particular, it is first suggested the use of BIM protocols at the design stage, to manage project information in a systematic way. At the execution phase a non invasive monitoring system and the application of procedural protocols, in charge of foremen or crews leaders, are used for resource and work progress tracking. Finally, the collected data are filtered to automatically produce daily site reports and other structured information.

The whole approach has the main objective of collecting information from the work progress at the construction site in real-time, to compare such information with the project baseline and to estimate performance indices. In order to accomplish that, project information will be created and organized using the BIM software language, which also includes the baseline. The same codes used to label construction elements in the BIM model, will then be encoded in the corresponding RFId devices, in order to identify the elements put in place.

Thanks to BIM adoption, the corresponding actual 4D model could be updated progressively over the work progress, thus reducing the management effort.

Work progress will rely upon the use of wireless sensors to easily generate and retrieve data. Fig. 2-1 provides a visual representation about how the procedure may be applied to the case of column erection. As soon as the crane puts in place the first precast concrete column, the crew leader or the foreman fixes one of the passive RFId tags labeled with the code relative to "columns" type (e.g. LE1COLO1xxx) and lot no. 1 on the same column (Fig. 2-1-a). The tags must be always available in the site's office. As this is a passive RFId tag, an RFId reader, equipped with a TX system, will be used by the crew leader to read the tag and transfer such reading together with its time and location to a local workstation (e.g. in the site office). Thus, the workstation will infer that one of the tasks of the "column erection" activity type has started in the position communicated by the RFId reader (e.g. position corresponding to lot no. 1 or sub-phase 1). Hence it will update the actual 4D visualization through the display of few columns in that lot and will store the related data in its database (for next reporting). At the end of the same task relative to the first lot (Fig. 2-1-b), the same crew leader or foreman will read that tag for the second time, meaning that such a task has been accomplished. Hence the server will integrate the actual 4D visualization by displaying all the columns connected to that lot, which are easily retrieved from the BIM model, through their codes. As a consequence, both the visualization and server's database are updated in realtime, just given the simple actions in charge of the foreman or crew leader, who are not asked to fill in paper documents and can save time in this way. Similarly, when the crew starts to put some columns in place in the second lot, another RFId tag of type 2 (e.g. LE1COLO2xxx) will be fixed and read (Fig. 2-1-c) and then read again at the end of the same sub-phase (Fig. 2-1-d). Updating of the actual 4D visualization and server's database will be performed as in the previous case. Figs. 2-1-e and 2-1-f are representative of the same process repeated in phase/lot no. 3 of the activity. To be noticed that the localization capability of the monitoring system is essential to infer where the RFId reading has taken place and which lot is under construction.

While this process is ongoing, the same system used for RFId localization may perform resources monitoring, in terms of number of hours of presence on site and their positions. The technology used for resources monitoring and communications is a wireless communication and localization sensor network, which is property of the Italian company Smart Space Solutions srl and developed as a part of this work.

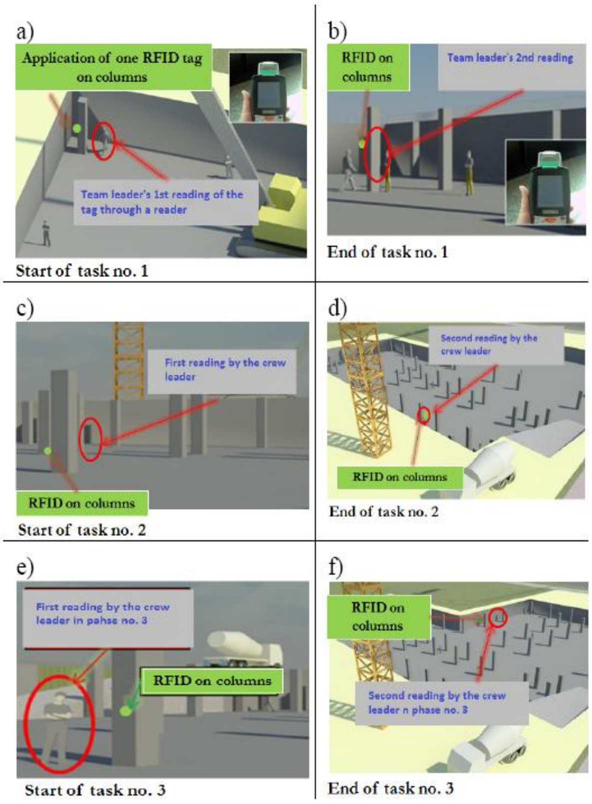


Figure 2-1 Work progress monitoring over the column

It is based on the IEEE 802.15.4 standard medium access and Zigbee stack communication protocol. It owns the advantages of working in ISM band, being reliable, self healing and easy to deploy, having low cost and low power consumption. It is made up of one or more coordinators used to initiate network formation, fixed devices with routing capabilities installed at known locations of the area under monitoring, and end devices (or tags) used as mobile nodes with associated IDs (Fig. 2-2). Localization is performed through the application of the "Weighted Centroid Localization" approach. Low power features of the network are assured thanks to a reduced routers' duty cycle in asynchronous mode. Each router remains in sleep mode for reducing power consumption until it has to route a message or reply to a request. In these cases an asynchronous signal wakes it up from sleep and allow it to work without wait for a sync[6].

The localization hardware engine and the low power communication capabilities, combined with its self-healing property, make this wireless sensor network extremely suitable in dynamic environments, as compared to other tracking technologies.

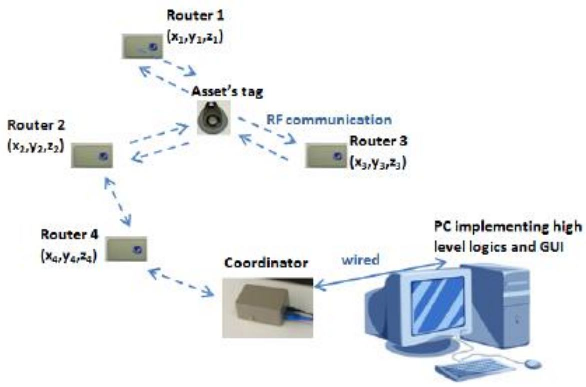


Figure 2-2 Low-invasive monitoring system architecture.

The most relevant information coming from such a monitoring is relative to activity progress and resources usage[6].

The system has been tested in a case study focused on the Design of Multifunctional Centre "Porta Lavagine" (Ex Agricultural Cooperative) in Urbino in Via Bocca Travaria.

As discussed above, in the second part of the work has been developed a Bayesian Network system for automated work progress estimation.

Bayesian Networks (BN) have the unique capability to provide both intuitive and scientifically rigorous representations of complex systems. In addition, after validation, they can be used for performing both scenario analyses, through inference propagation algorithms, and diagnostic reasoning, through back-ward propagation based on the inversion rule.

These networks also have the advantage of enabling qualitative and explicit representation, where nodes represent variables and arcs represent quantitative relationships among the same, worked out through parametric probabilistic models.

When the domains to be modeled are very complex, Object Oriented Bayesian Networks (OOBN) are usually used: they are made up of several elementary networks, sharing some of the variables, which constitute the links between the networks. Each elementary network is generally developed separately (and models one of the involved many physical phenomena) but the inference algorithms are propagated over the whole set of elementary networks.

Dynamic Bayesian Networks (DBN) are used to represent statistical models that depends on time, usually called stochastic processes. DBN are based on a discretized time line, and are made up of several time slices, each representing a snapshot of the state of the system at a particular moment in time. Transition relationships among different state variables in different time slices capture the system temporal dynamic. The application of BNs to model the evolution of processes that have temporal dynamics requires, in its simplest formulation:

- an initial instance of the Bayesian network that contains the formulation of the problem at time t=0, that is the set of random variables $X_{i,0}$ and the related conditional probability distributions: $P(X_{i,0}|X_{i-1,0})$, $P(X_{i-1,0}|X_{i-2,0})$, etc.;
- one or more transition networks that correlate the variables of the BN instance at t=0 with the variables of the BN instance at t=1.

Fig. 2-3 shows a graphical representation of three time slices of a DBN.

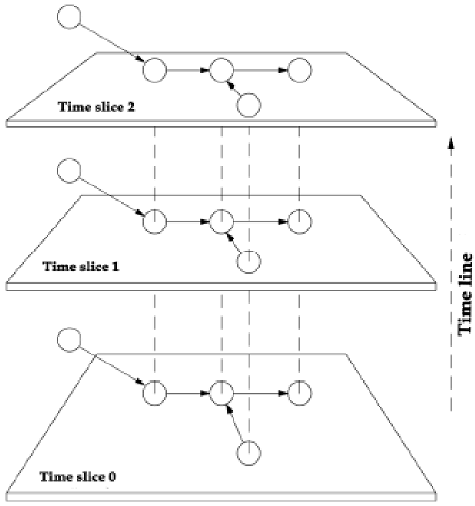


Figure 2-3 Graphical representation of a general Dynamic Bayesian Network: it is made up of three instances of the same BN.

Two assumptions are usually made about the physical processes at hand:

- all the information needed to predict the state of the process at time t+1 is contained in the description of the process state at time t. No information about earlier time is needed. These kinds of processes are called Markov processes of or-der one;
- the process is steady, that is, the transition net-works remain the same for any ti → ti+1.

The resource usage data, that have been feeded to the progress estimation algorithm, have been collected by monitoring the execution of a shopping mall in the village Cerreto d'Esi (AN), built by the company Torelli & Dottori SpA. The whole project includes three areas: the shopping mall, the office building and the parking lot. Our monitoring was relative to the erection of the shopping mall.

Three tasks have been monitored during the execution:

- excavation and pipelines laying (sewage, electrical power line, water supply), both external and internal;
- site cast ground floor concrete slab;

-fabrication of internal hollow brick partitioning walls.

As relevant variables for work progress monitoring were not know *a-priori* before the development of probabilistic models, monitoring was performed by operators observing the work progress and writing down records every 5*min* relative to the use of the resources listed above. This approach allowed redundancies and boost awareness on the procedures performed on site. So for each of the monitored tasks the following documents have been produced:

- a database comparing the work progress with the amount of resources employed during a time duration of 5*min*;
- reports with description of the work performed and monitored data;
- a photographic survey of the activities.

Id	excavator (%/60 min)	excavation man-hours	excavation progress	pipelines man-hours	dumper (%/60min)	pipelines progress	truck (%/60 min)	dumper (%/60 min)	trench filling progress
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.77	0.58	5.00	1.50	0.00	5.00	0.08	0.00	0.00
3	1.00	0.17	15.00	2.17	0.00	10.00	0.08	0.17	10.00
4	1.00	0.25	10.00	2.92	0.00	10.00	0.00	0.25	5.00
5	0.57	0.00	20.00	1.42	0.00	10.00	0.29	0.00	0.00
6	1.00	0.00	5.00	1.00	0.00	5.00	0.00	0.00	0.00
7	0.00	0.50	0.00	2.58	0.00	10.00	0.00	0.92	20.00
8	0.50	1.00	0.00	1.00	0.00	0.00	0.08	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	0.85	0.10	20.00	0.17	0.54	20.00	0.00	0.00	0.00
11	1.00	0.08	25.00	2.83	0.54	30.00	0.00	0.00	0.00
12	0.92	0.15	25.00	4.25	0.58	40.00	0.00	0.00	0.00
13	0.42	0.10	25.00	2.67	0.08	20.00	0.17	0.00	20.00
14	1.00	0.15	25.00	0.67	0.00	20.00	1.00	0.00	30.00
15	1.00	0.07	20.00	0.17	0.00	12.00	1.00	0.00	30.00
16	1.00	0.08	25.00	2.08	0.00	20.00	0.67	0.00	30.00
17	1.00	0.08	10.00	1.33	0.00	20.00	0.00	0.00	0.00
18	0.00	0.00	0.00	0.75	1.00	0.00	1.00	0.00	0.00
19	0.00	1.08	0.00	4.58	0.00	10.00	1.00	1.00	10.00
20	0.00	1.08	0.00	3.25	0.00	5.00	1.00	1.00	10.00
21	0.00	1.00	0.00	4.08	0.00	5.00	1.00	1.00	10.00
22	0.00	1.00	0.00	7.75	0.00	15.00	1.00	1.00	10.00
23	0.00	0.58	0.00	3.83	0.00	10.00	1.00	1.00	10.00
24	0.00	0.50	0.00	2.92	0.00	10.00	1.00	0.83	5.00
25	0.00	1.00	0.00	6.75	0.42	20.00	1.00	0.00	5.00
26	0.00	1.00	0.00	6.58	0.00	10.00	1.00	0.42	10.00
27	0.00	1.00	0.00	6.83	0.00	5.00	1.00	0.25	10.00
28	0.00	1.00	0.00	1.25	0.00	0.00	0.25	0.00	5.00
29	1.00	1.58	0.00	0.17	0.23	0.00	0.00	0.00	0.00
30	1.00	1.58	30.00	0.00	0.00	0.00	0.23	0.00	35.00
31	1.00	1.58	30.00	2.42	0.00	20.00	0.00	0.00	0.00
32	1.00	1.17	30.00	1.75	0.00	20.00	0.43	0.00	30.00
33	1.00	1.08	30.00	1.50	0.00	20.00	0.00	0.00	0.00
34	1.00	2.67	30.00	2.58	0.00	30.00	0.75	0.00	20.00
35	0.83	1.42	20.00	2.83	0.00	30.00	1.00	0.00	45.00
36	1.00	0.42	20.00	1.00	0.00	0.00	0.00	0.00	0.00
37	0.75	0.06	15.00	2.50	0.25	10.00	0.42	0.00	20.00
38	0.00	0.08	0.00	0.33	0.00	0.00	0.00	0.00	0.00
39	1.00	1.58	0.00	0.17	0.23	0.00	0.00	0.00	0.00
40	0.58	1.08	25.00	2.67	0.00	20.00	0.00	0.00	0.00
41	0.67	0.67	10.00	3.00	0.00	15.00	0.33	0.00	10.00

Figure 2-4Hourly dataset worked out from the database collected during the execution of excavation and pipe-lines.

A pre-processing phase showed that a sampling time of one hour is short enough to capture all the relevant dynamics of the monitored activities. In addition the task under analysis has been subdivided into the three sub-tasks:

- trench excavation;
- laying of pipelines on a concrete bed;
- trench filling with sand and previously excavated ground.

That's because the overall work progress of the main task resulted in fact from the composition of the work progress of these sub-activities. Therefore the data initially recorded have been resampled with a time scale of 1 hour (i.e. the time of equipment usage and the man-hours has been summed). Photos, site reports and measurements allowed to assign the actual work progress to each working hour. The data in Figure 2-4 have been consequently organized through 41 rows (one for each hour) and 9 columns: three devoted to the work progress of each sub-task and other six devoted to resource usage during their execution.

These data have been used to train the Dynamic Bayesian Network Model.

Fig. 2-5 depicts a plot of the work progress versus man-hours in the case of excavation sub-task. Similarly to the other sub-tasks (laying of pipelines and trench filling) it's clear that no functional dependence can be defined established by the two variables, Hence the processes must have be modeled as stochastic Markov processes. Both first-order and second-order Markov networks have been tested, showing that the second worked better.

Networks development followed three steps:

- the qualitative network relative to a second-order Markov process for each of the sub-tasks has been developed;
- the dataset has been rearranged to train the network according to the above defined variables and the NPC structural learning performed to find out other hidden causal relationships;
- the EM learning process has been performed by means of the Hugin Expert ™ software and demonstration of reliability carried out.

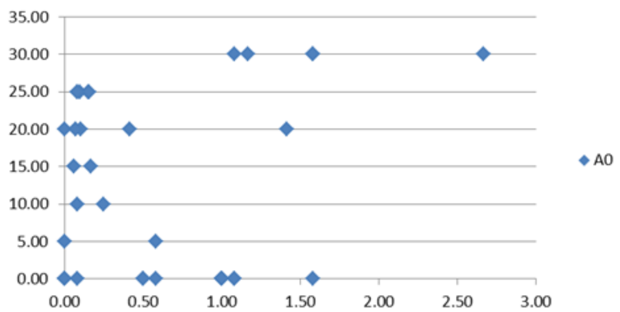


Figure 2-5 Work progress plotted vs man-hours relative to the excavation sub-task.

Fig. 2-6 depicts the structure of the DBN relative to the excavation sub-task; the meaning of the nodes being as follows: A = work progress; B = equipment usage; L = amount of man-hours. The second digits (i.e 0, 1, 2 and 3) are referred to the time slice: for example L0 is the amount of man-hours used the hour before L1 and two hours before L2. It can be noticed that in each time slice the work progress (A) has been assumed as conditionally dependent upon man-hours (L) and equipment usage (B). In addition every variable in each time slice is influenced by the value of the same variable in the two previous time slices (e.g. A2 is dependent on A1 and A0): this is the translation of a second-order Markovian process into a Dynamic Bayesian Network.

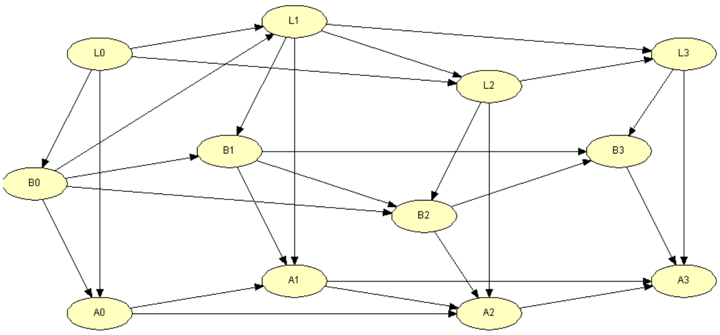


Figure 2-6 Initial qualitative representation of a sub-network.

Then the dataset in Figure 2-4 has been rearranged to replicate each variable in the four time slices (e.g. L0, L1, L2, L3) with a shift of 1 hour each time slice and NPC structural learning performed. This algorithm allowed us to test whether other conditional dependence relationships occurred among each pair of variables, through an independence test, which is performed according to equations:

$E(x_{ij}) = (x_{i+} \cdot x_{+j}) / n$ (1)

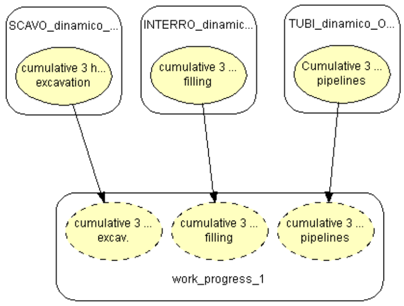
$E(x_{ijk}) = x_{i+k} \cdot x_{+jk} / x_{++k}$ (2)

Referring to eq. (1), it is run on a dataset of *n* records, where x_{ij} is any record. x_{i+} is every observation where x is found with a given value and the same holds for x_{+j}. If the two variables are conditionally independent, their mean value for the generic x_{ij} must be given by equation (1). Eq. (2) holds on the same bunch of theory, but considers marginal probability distributions where dependence of the variable x_i from x_j is surveyed once the value of x_k is given. The use of eqs. (1) or (2) depends on the kind of qualitative relationships assumed among the variables. The statistics is distributed as a "chi-squared".

Then has been created 3 sub-networks relative to: excavation, pipeline laying and trench filling.

At this juncture the dataset was used to perform EM learning[16] for each sub-network: this kind of learning is capable of estimating multivariate "Dirichlet" distributions describing every conditional relationships in the network, the order of the distribution of each variable (or node) being as high as the number of parents (i.e. incoming arrows) pertinent to any variable. The final qualitative structure of the OOBN capable of mixing all the inputs and computing the expected overall progress in given in Fig. 2-7-a: the three sub-networks discussed above give as outputs the single work progress, which is passed through the OOBN in Fig. 2-7-a to the sub-network in Fig. 2-7-b, where the overall work progress is then computed as a weighted input from each of the sub-networks. [18]

a)



b)

Figure 2-7 Qualitative structure of the overall work progress network (a) and sub-network for the computation of the work progress (b).

3 Analysis and discussion of main results

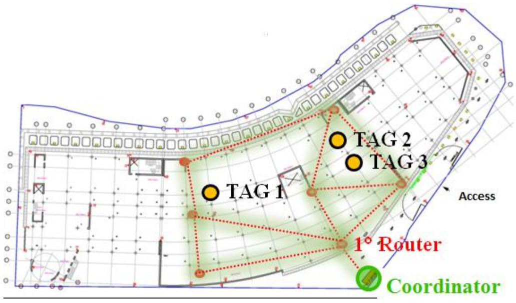
As discussed in the paragraph above, the two sub-systems have been tested separately. Now the results are discussed and analyzed, focusing the attention on the original contributions given by this work.

The localization sub-system has given good result in the process of automatic data gathering in the test construction site (Multifunctional Centre "Porta Lavagine").

Although the whole procedure has not been fully tested, yet some preliminary experiments have been executed in order to evaluate how data regarding resource allocation may be retrieved and filtered to obtain structured information and automated Daily Site Reports (DSR). The wireless system described in sub-paragraph above was installed on a 1200 m_2 portion of the site depicted in Fig. 3-1-a, as shown in part b of the same figure, relative to the erection of a building targeted to parking areas and commercial activities. Then three tags were deployed: tag no.1 was give to one worker, tag no. 2 was fixed inside a dumper and tag no. 3 inside an excavator. As a first trial it was tested that positions were correctly estimated, like in Fig. 3-2-a, obtaining successful results. A software application at the server level was set up, for automatic production of daily site reports. The data retrieved from the site are stored and associated to the resources positions over time. Then they are filtered and elaborated to provide a first version of daily site reports in an automatic way. In particular, it is expected that at the end of any working day, every crew leader will input the list of tag codes associated with the workers of their crew.

The system will automatically set a daily site report as shown in Fig. 3-2-b (both in its digital and paper version), where the time of permanence of the resource on site is reported, together with the site's data and the list of pieces of equipment concurrently present on site. The paper version of the report has been predisposed to give users the opportunity to make corrections or integrate it with further information, if needed.

a)



b)

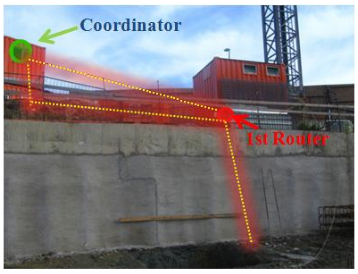


Figure 3-1 On-site system installation.

At this stage the part of the reports regarding the list of activities where each worker has been involved in, has been left blank, because it will be filled in when a further research step in the monitoring procedure described above will be accomplished.

Similarly, other sensing technologies will be developed to automatically associate the actual usage period of equipment and the corresponding operators. As a first idea, vibration sensors will be integrated in the tags installed on the machines in order to record their actual working time.

a)

b)

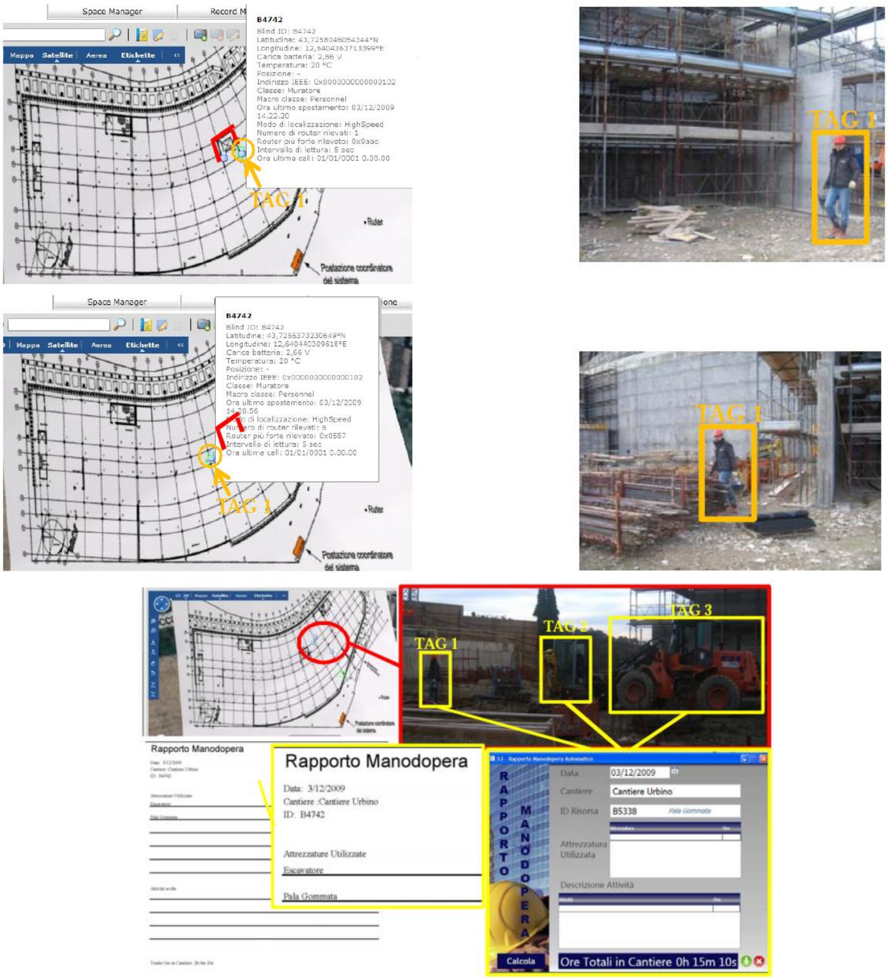


Figure 3-2 Localization accuracy estimation and daily site

When they are turned on, proximity queries will be sent by the tags in the machine, in order to select those operators who are inside and forward such information to the local server. In this way, the daily site report's lines regarding equipment usage by workers will need no more to be filled in by operators, but will be automatically managed[6].

Now are discussed the results of the testing of the Dynamic Bayesian Networks developed starting from the data gathered in the test construction site ("Shopping mall in the village Cerreto d'Esi").

The three sub-networks developed in the previous sub-section are able to model the processes under analysis. To this aim the networks have been used in the running modes and their inferences compared to the dataset.

Fig. 3-3 shows how validation was performed: the variables on the left with red rows are those ones where evidences have been inserted, that is to say the state of the variables have been observed and fixed in the networks.

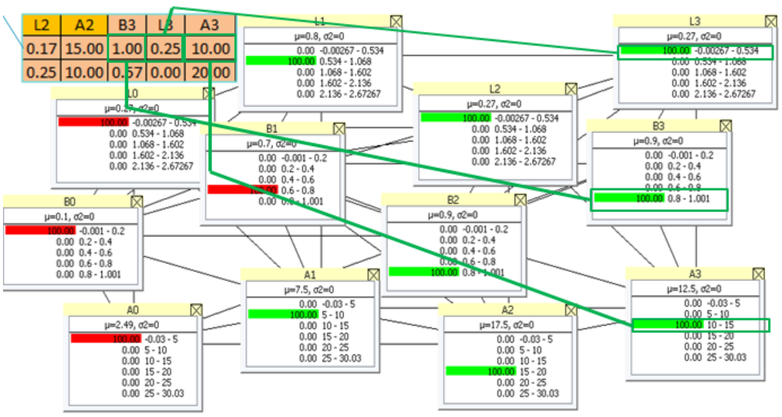


Figure 3-3 One of the validation cases for the sub-network relative to the excavation phase.

Then the network performs inferences on the future states (time slice no. 3) and gives back the intervals depicted in Fig. 3-3, which are in accordance with the dataset. In Fig. 3-4a and 3-4b two other validation cases for the same sub-network are shown. It came out that the three sub-networks are capable of representing the process and restituting the non-linear relationships holding between the variables and regarding the work progress on the considered construction site.[18]

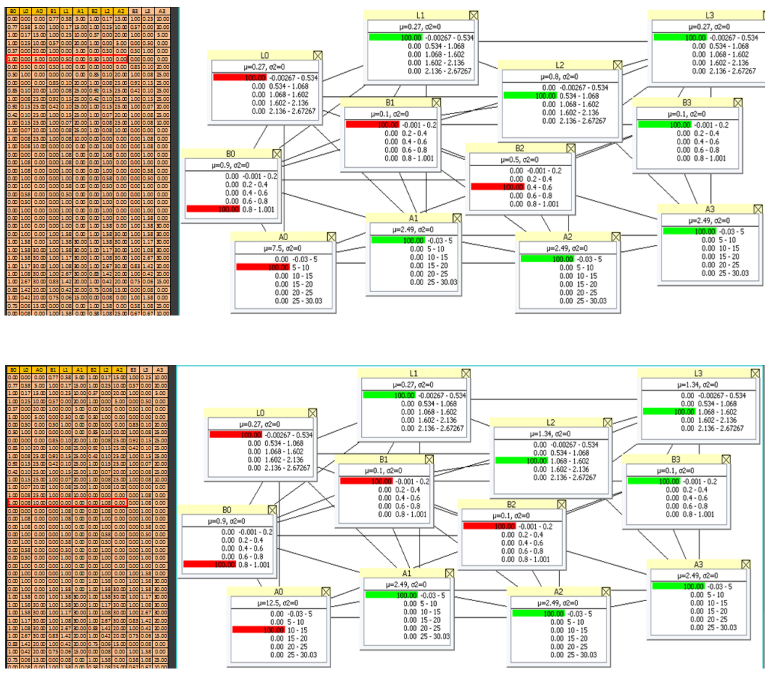


Figure 3-4 Two validations where estimations by the sub-network have been compared to the database.

4 Conclusions

The main aim of this work was the development of an automated system that supports the construction companies, providing real information about the progress of the work.

The concept of quality is increasingly recognized as a "value" in all areas and construction, for importance and complexity, can not be excluded. The study addressed begins with the internal observation of a construction company and the analysis of the procedures used by the same company for the attainment of the "overall quality".

This first approach has allowed us to find weaknesses common to many companies: the most obvious are the limited availability of resources, resulting in the possibility of carrying out inspections only in critical situations with the limited progress reports, found in steps a day or week. This is definitely not enough to fit into standard quality, as the search for "overall quality" certainly needs more information. This preliminary study has led us to look for a support that can help companies in pursuing the goal of the highest quality.

The approach for monitoring of construction progress presented in this work is based on three main pillars: semi-automated monitoring of activity progress, automated estimation of resources allocation through non-invasive technologies and real-time work progress estimation through Bayesian networks.

This work has assessed a procedure based on BIM modeling useful at the design phase to organize information, so that it facilitates the next monitoring phase.

Then it has been tested how resources can be monitored and the corresponding information automatically reorganized in support of construction managers and inspectors.

Finally it has been developed a Bayesian network which aim is to predict work progress starting from a dataset built with collected data in a defined period of time. One of the difficulties lays in the need to decompose the tasks into sub-tasks and find out causal relationships among the involved variables so the whole progress may be estimated. In the case of construction sites there is no linear dependence (or functional relationship) between the resources employed at every hour and the work progress. So it was necessary to work out Bayesian networks representing second-order Markovian processes, whose causal relationships have been modeled through the EM learning algorithm, based on the use of Dirichlet probability functions. As it was demonstrated, the relative sub-networks well represents the several processes as probabilistic inferences are within the observations recorded in the dataset. Finally the qualitative structure of the overall network, working out the progress estimation has been proposed. Future steps will be relative to validations of the overall network and inferences per-formed with respect to tasks spanning longer time periods.

This work has presented two separated systems that in future can be unified in one platform that will have the capacity of use localization monitoring data to automatically fill the data that will be used by the Bayesian Network system. This integrated system will create a powerful instrument useful to manage a construction site in full automated way.

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