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APPLICATION OF NEW INFORMATION TECHNOLOGY ON CONCRETE: AN OVERVIEW

Bakhta Boukhatem[1], Said Kenai[2], Arezki Tagnit-Hamou[3], Mohamed Ghrici[4]

[1, 2]Laboratory of Materials and Civil Engineering, Department of Civil Engineering, University of Blida, Route de Soumaa Blida, BP 270 Blida, Algeria
[3] Department of Civil Engineering, University of Sherbrooke, 2500 Sherbrooke, J1K 2R1, Canada
[4] Department of Civil Engineering, University of Chlef, BP 151 Chlef, Algeria
E-mails: [1]Bakhta.Boukhatem@USherbrooke.ca; [2]sdkenai@yahoo.com (corresponding author); [3]A.Tagnit@USherbrooke.ca; [4]mghrici@gmail.com

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Abstract. The development of information technology provides means for quick access to a wide variety of information and methods of modelling complex systems. Simulation models, databases, decision support systems and artificial intelligence have currently become more accessible. Advances of these techniques continue to impact highly on civil engineering. The aim of this paper is to present recent developments in information technology and their influence on concrete technology. A historical perspective on researches and a review of the application of artificial intelligence techniques on concrete are presented. Development of computer integrated knowledge systems, approach of virtual systems and software for concrete mix design are also discussed. These systems have greatly affected handling tasks in civil engineering design over the past decade and promise to have revolutionary impacts on the nature of the design tasks in the future. They are considered useful and powerful tools which are able to solve complex problems and represent a scientific challenge in concrete technology.

Keywords: information technology, simulation models, artificial intelligence, computer integrated knowledge system, virtual system, concrete mix design.

1. Introduction

The rapid development of computers and information technology provides means for quick access to a wide variety of information and methods to model complex systems. These developments have become an essential part in almost every discipline. In concrete technology, these techniques allow researchers, engineers, and concrete practitioners to develop, store, search, integrate and spread knowledge on all aspects of concrete. Simulation models, databases, decision support systems and artificial intelligence (expert systems, neural networks, fuzzy logic and genetic algorithms) have become more accessible. Advances of these techniques continue to have a high impact on civil engineering. These developments have attracted many researchers to work on advancing the use of these techniques to cover a wide range of applications. This paper presents an updated literature review of these new techniques and their applications in concrete technology. This includes existing simulation models, artificial intelligence techniques, computer integrated knowledge systems, virtual systems approach, and concrete mix design software. Before giving a corresponding historical overview of these techniques, a brief history of computer applications in concrete technology is presented in the next section to provide the background context of this study.

2. Brief history of computer applications in concrete technology

Concrete is the most widely used construction material in the world. It is a nonlinear composite material often viewed as complex and unpredictable. Because of this complexity, primary analytical methods to quantify the relationship between its microstructure and its properties were unsuccessful. A promising alternative appeared by computer simulation models. This simulation applies to concrete and is called Computational Materials Science of Concrete (CMSC) (Garboczi *et al*. 2000). This technique was supported with the development of the first and the most advanced digital image model on the Cement Hydration in three Dimension (CEMHYD3D) (Bentz 2005). Based on this model, the National Institute of Standards and Technology (NIST) issued a challenge to build the Virtual Cement and Concrete Testing Laboratory (VCCTL) in order to reduce the number of test mixes and specimens on cement and concrete with desired properties in the field tests (Bullard *et al*. 2005).

Meanwhile, other models were proposed for concrete mix design to predict its properties. As a result, the Central Laboratory of Bridges and Roads (LCPC) developed software consisting of a set of models to aid practitioners in concrete mix proportioning (De Larrard and Sedran 2007). In addition, and at individual level, several researchers focused on the application of techniques of artificial intelligence to design their models in prototype system form (Clifton and Frohnsdorff 2001; Issa and Anumba 2007).

Therefore, a high collaboration between the experimentalists and the designers to develop such systems was needed. This trend of collaborative research reinforced links between different research communities such as the American Society in Civil Engineering, the NIST Information Technology Laboratory and the European Group for Intelligent Computing in Engineering (Moore and Miles 2003).

3. Simulation models for cement and concrete based materials

Several simulation models have been developed to address problems related to the characterization of concrete and the prediction of its performance. First, most models addressed hydration of silicates and aluminates and few Portland cement hydration models were reported. However, based on the CEMHYD3D model, the development of cement hydration models takes currently a double way: improving the scientific basis of chemistry and physics, and improving and/or modeling systems hydration of concrete containing mineral additives such as slag and fly ash (Chen *et al*. 2007). Fig. 1 shows respectively, false color image, produced by scanning electron microscopy and x-ray microscope analysis, illustrating the various chemical phases in individual cement particles and a three-dimensional image showing virtual cement particles mixed in water just prior to the start of hydration.

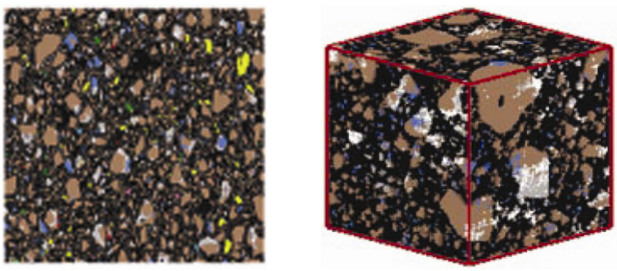


Fig. 1. 2D and 3D image of cement particle presentation by CEMHYD3D model (Bentz 2005)

The modeling of the early-age properties of cement-based materials including the visco-elastic behaviour and elastic modulus of concrete were reviewed by Bentz (2008). In addition, models for predicting concrete compressive strength were developed. For early age concrete, the literature highlighted methods of developing maturity concept, which was first introduced by Nurse (1949) and Saul (1951). Later, Chanvillard and D'Aloia (1994) described a model for predicting early age concrete compressive strength using the equivalent time method. For the prediction of the 28 days concrete compressive strength, several models were developed using Féret and Bolomey formulas. Numerical modeling of shrinkage and creep of concrete has also been developed (Gawin *et al*. 2007). Currently, concrete practitioners have a particular interest to produce a sustainable concrete. Therefore, several models have been developed for estimating the concrete durability (Bentz 2007).

4. Databases

Databases are used extensively in many application areas and especially in the engineering field. They are defined as systems in which it is possible to store large amount of information or data in a structured way on a permanent support and with the least possible redundancy. Thus, the concept of database is generally connected to the network in order to share information and provide access to multiple users simultaneously. This type of database is called distributed databases (Ozsu and Valduriez 1999).

In concrete technology, a Database (DB) can efficiently store and update concrete research results. However, developing a DB for concrete requires considerable effort and specialized skills. Thus, Internet has created a new dimension for the use of DB. In this context, important considerations for the calibration of formats and quality of concrete data are to be considered. Also, standards and guides on data formats of concrete have been proposed (Oland and Ferraris 2000). Fig. 2 shows an example of a database on the properties of cement that has been implemented at NIST.

The first database in concrete was bibliographic. Later, one of the first attempts to collect numerical data on High-Performance Concrete (HPC) was developed by the University of California (William and Chi 1993). In Canada, a DB is developed on concrete exposed to a marine cold environment (Kondratova *et al*. 1998). Another DB on concrete with additives is available online where the data was collected from the experimental results achieved in various research institutions in Japan by Noguchi (2007). In recent years more complex structure DBs, have just started to develop such as intelligent and inductive DB (Meo *et al*. 2005).

5. Artificial Intelligence

The technology of Artificial Intelligence (AI) provides techniques for developing systems for simulating human problem solving. Among these techniques: Expert Systems (ESs), Artificial Neural Networks (ANNs), Fuzzy Logic (FL) and Genetic Algorithms (GAs). The synergistic combination of these techniques using models and intelligent tools in one environment has led to the emergence of Computer Integrated Knowledge Systems (CIKS). The improvement, use and increasing consultation of these systems has led to the development of new systems called the Virtual Testing Systems for potential application in all fields of engineering. In civil engineering, these systems are considered useful and powerful tools which are able to solve complex problems, especially in concrete technology.

5.1. Applications of Expert systems (ESs)

ESs are computer programs designed to model the problem-solving ability of human experts. They utilise observed or available information to produce 'high grade'

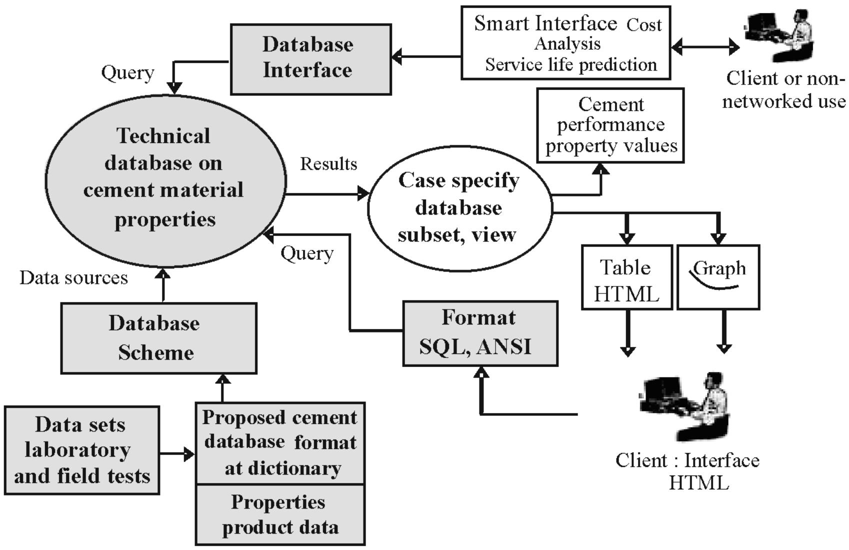


Fig. 2. Proposed database on cement properties (Oland and Ferraris 2000)

knowledge and solve problems by qualitative reasoning using the heuristic knowledge of a human expert. Most of these systems experts are rule-based systems which are based on mathematical foundations (Giarratano and Riley 2004). They consist of two principal elements: the knowledge base and inference engine (Fig. 3). The knowledge base includes specific knowledge scope. It can either be provided directly and updated by experts, or accumulated by the system itself over the experiments. The inference engine is a relatively general program, which from rules and facts, generates new facts in order to achieve effective resolution of the problem.

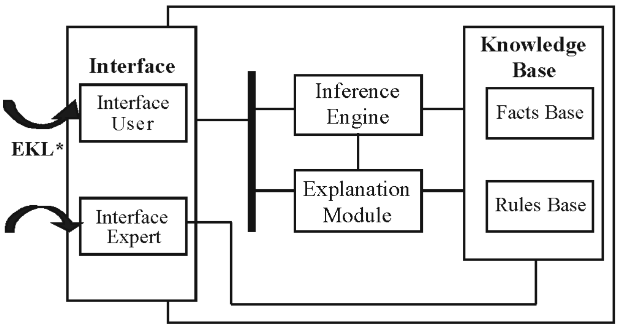


Fig. 3. Organization of expert system principle

In general, expert systems are more effective in limited areas in which solutions are well defined. In addition, they are best developed in areas where the knowledge base is relatively stable; otherwise, they may be obsolete before being accomplished. In civil engineering, ESs are applied in several areas particularly for diagnosis, choice, planning, control and Computer Aided Design (CAD). For example, a Highway Concrete expert system (HWYCON) (Kaetzel *et al*. 1993) was developed to identify the causes of disorders in roads and concrete bridges and recommend repair. This technology has been also adopted for an expert system for High Performance Concrete Mix design called HPCMIX (Zain *et al*. 2005). A brief review of these systems is available elsewhere (Islam *et al*. 2002).

A significant number of expert systems have been developed to design a durable concrete (Byars *et al*. 1996; Lv *et al*. 2003). Currently, expert systems are developed to make concrete resistant to corrosion and sulphate (Hao *et al*. 2004). Some expert systems are available on the Internet for the durability of reinforced concrete (Gomez and Garay 2005). Expert systems in form of Computer Aid Design (CAD) have allowed engineers and architects to develop models adapted to customers' needs. For example, VK.EXPERT and Durable Concrete (DURCON) are respectively CAD expert systems which have been developed for preliminary design (Syrmakezis *et al*. 1996), and construction of reinforced concrete buildings (Clifton *et al.* 1985). New expert systems connected with databases (Xia *et al*. 2005), neural networks (Gupta *et al.* 2006), probabilistic and fuzzy models, and various types of mathematical models (Zhong *et al*. 2006) have also been proposed.

5.2. Application of Artificial Neural Networks (ANNs)

ANNs were developed to model the human brain (Fig. 4). They have some powerful characteristics in knowledge and information processing and are capable of learning and generalizing from examples and experiences. This makes ANNs a powerful tool for solving some of the most complicated problems. The majority of their applications used the back-propagation multi-layer network (Flood and Kartam 1994).

In terms of learning (or training) algorithms, two broad classes have been defined depending on whether the learning is called supervised or unsupervised. This distinction is based on the learning examples form (couples input/output-related) presented to the multilayer networks in the case of supervised learning, whereas we have only the input values for the unsupervised learning in the case of dynamic (or recurrent) networks. At the end

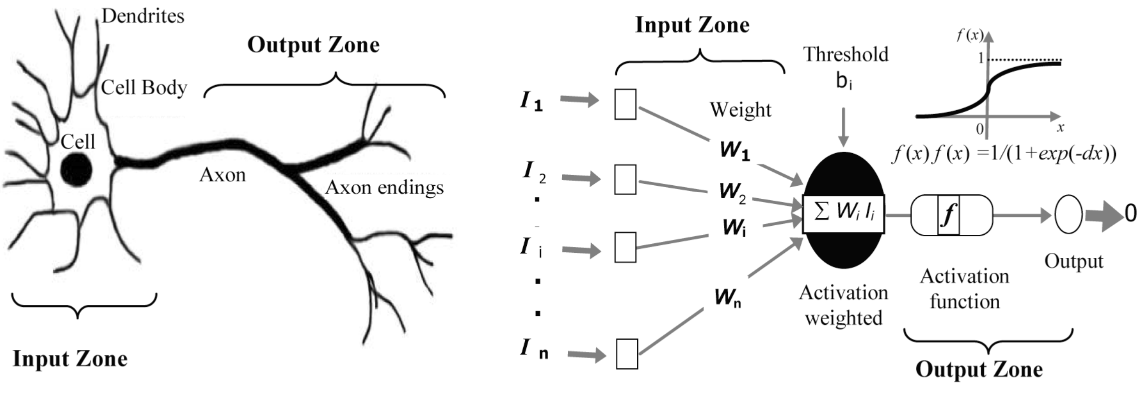


Fig. 4. Modeling of biological neuron

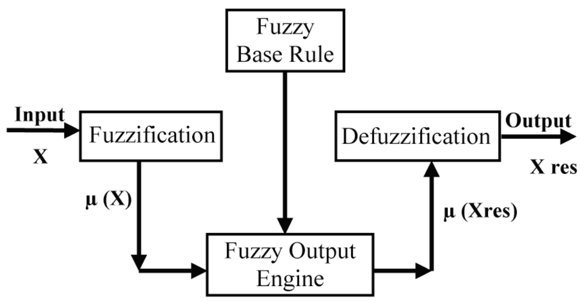
of training, the weights are fixed, and then the network is prepared for use. In general, training a network takes a period relatively long in time (training phase). During this period, the vectors of input neurons can be presented to the network in a number of times (cycles or iterations). The determination of the training parameters during the training phase is the most important phase for developing an ANN such as the learning rate, learning error and the number of iterations. There is also a validation or test phase for testing the performance of the trained network. Upon completion of the validation and the test processes, the network should be able to give out the solution(s) for any set of data based on the general architecture that has been developed.

In recent years there has been a growing interest for ANN. These have found applications in almost all disciplines of science and engineering to solve optimization problems, classification, identification, and forecasting (Dreyfus *et al*. 2002). Applications of ANN in civil engineering have been widely used in the late 1980s (Flood and Kartam 1994; Moselhi 1996). Several research works have clearly shown the potential and applicability of ANN models in solving problems of structural, geotechnical and concrete technologies. Manik *et al.* (2008) investigate the use of ANN to build surrogate models for a pavement construction payment-risk prediction model. In concrete technology, their application mainly concerns the formulation (Oh *et al.* 1999; Yeh 2009), hydration (Basma *et al*. 1999; Parka *et al*. 2005; Subasi *et al*. 2009), workability (Bai *et al.* 2003; Yeh 2006), compressive strength (Pala *et al*. 2007; Bilim *et al*. 2009; Sarıdemir 2009; Sarıdemir *at al.* 2009; Prasad *et al.* 2009), elastic modulus (Demir 2005; Demir 2008) and durability (Hewayde *et al*. 2007; Parichatprecha and Nimityongskul 2009) of concrete. Other applications have proposed models for computer-aided design for optimum concrete mixture including also other types of concrete (Ji *et al*. 2006). For example, Lee (2003) proposed a modular architecture composed of five ANNs for predicting concrete compressive strength.

5.3. Application of Fuzzy Logic (FL)

FL concept which was first introduced by Zadeh (1996) provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables. It performs numerical computation by using linguistic labels stimulated by membership functions and linguistic fuzzy rules.

A general fuzzy system is presented in Fig. 5. According to this figure, the implementation of a fuzzy control shows three major modules. The first module (Fuzzification) is attributed to the actual value of each entry, at time t and its membership function μ. The second module (Fuzzy Rule Base) is the application of rules such as (IF...THEN...). The inference engine takes into consideration all the fuzzy rules in the rule base and learns to transform a set of inputs corresponding to the results. The third and final module (defuzzification) is the reverse transformation of the first module. It skips a membership degree of a command to determine the value to give to this command. It means converting the fuzzy results to actual results by defuzzification methods.



X : the input vector, X_{RES} : the input commands, μ(x) and $\mu(X_{RES})$: the correspond memberships functions

Fig. 5. The fuzzy logic modelling process

This powerful tool has been successfully used in many research areas. In civil engineering, it was first applied in cement industry for intelligent control of grinding cement kilns (Lin *et al*. 1996). It was also used for fatigue resistance of steel structural members under bending (Kala 2008) and for contractor prequalification (Plebankiewicz 2009).The prediction of compressive strength and modulus of elasticity of ordinary and high-strength concrete using FL has also been reported (Uygunoglu and Unal 2006; Demir 2005). Furthermore, combination of ANNs and FL has been widely used

(Topçu and Sarıdemir 2008a). Another model predicting compressive and flexural strengths of concrete containing silica fume and recycled aggregates has also been developed (Topçu and Sarıdemir 2008b).

5.4. Application of Genetic Algorithms (GAs)

GAs method, which was first formalized as an optimization method by Holland (1992), is a global optimization technique for high dimensional, nonlinear, and noisy problems using a stochastic search technique. It is based on the mechanism of natural selection and natural genetics and it is known as a very efficient heuristic algorithm.

Fig. 6 shows the various operations involved in a basic genetic algorithm. From this figure, at each iteration or generation, a new population with the same number of chromosomes is created. This generation consists of chromosomes better "adapted" to their environment as represented by the selective function. With development of generations, the chromosomes will tend towards the optimum of the selective function. The creation of a new population from the previous one is done by applying the genetic operators that are selection, crossover and mutation. The selection of the best chromosomes is the first step in a genetic algorithm. During this operation the algorithm selects the relevant factors that optimize the function. The crossover is used to generate two new chromosomes "children" from two chromosomes selected "parents", while the transfer makes the inversion of one or more genes from one chromosome.

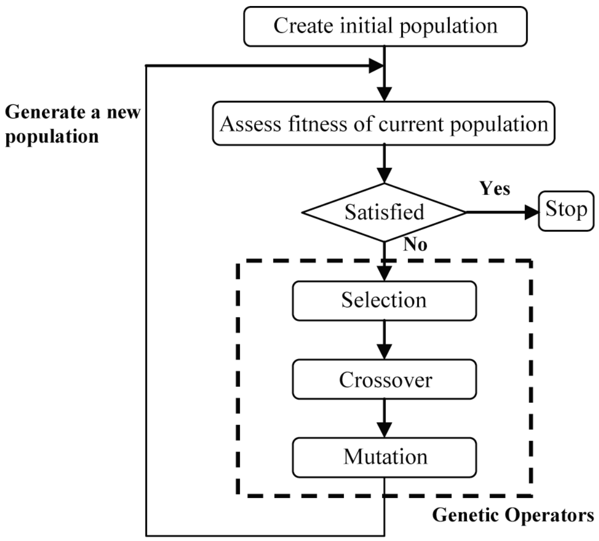


Fig. 6. The process of genetic algorithm

GAs have been widely used in various fields of engineering and they have given more accurate results than other algorithms in concrete mix proportioning. For example, Lim *et al*. (2004) have used the GAs method for optimizing the formulation of HPC mixtures. The GAs have also been used as optimization techniques for ANNs (Xiaodong *et al*. 2007). Currently, the combination of AI approaches has produced new systems for improving CIKS (Gupta *et al*. 2006).

6. Technology of Integrated System

Computer Integrated Knowledge System (CIKS) is an intelligent system of integrated empirical and heuristic knowledge to solve complex problems. It includes DBs, simulation models, AI systems, manuals and codes. With such knowledge bases, a CIKS includes ways to obtain knowledge of distributed sources of knowledge using the Remote Database Access (RDA) and agents (Brady and Sullivan 1996). To answer some desired features of a CIKS, it must be open, in which the performance is independent of the computer system; interactive with a graphical user interface; capable of acquiring knowledge and data from distributed systems; easy to assimilate new knowledge and integrity; and validated with a fully integrated architecture that provides the automatic transfer of knowledge through system interfaces.

CIKS technology is applied to concrete by the development of several prototype systems. A prototype to predict the service life of reinforced concrete structures was developed (Bentz *et al*. 1996) as well as system for High Performance Concrete (HPC) (Clifton *et al*. 1997). The system consists of a series of web pages (HTML), which can be accessed over the World Wide Web. It involves an extension of the first version of CIKSBHP system that was designed to predict the diffusivity of chlorides and the service life of concrete based on Portland cement where the corrosion of steel is the primary mechanism of degradation. The system is improved and updated periodically and is integrated in the virtual testing laboratory of cement and concrete developed by NIST (Fig. 7).

7. Virtual Cement and Concrete Test Laboratory (VCCTL)

The collaboration between three research laboratories at NIST led to the creation of a new VCCTL (Bullard *et al*. 2005). The main objective of this laboratory is the development of software using a set of integrated modules. The software simulates the microstructure of concrete and hydration processes, and predicts many physical and mechanical properties of cement and concrete based on detailed knowledge of the microstructure of well characterized materials, curing conditions, and environmental factors.

The development of integrated models in VCCTL is based on 3D microstructure approach. The microstructure is obtained by a spatial resolution at each sub-particle elements on low volume 1 $\mu\ m^3$ (Fig. 8). Fig. 9 shows the range of input specifications and predicted properties for the current VCCTL software modules. The concept of VCCTL cannot, and is not intended to replace the experimental trials. Studies have illustrated the power and the flexibility of the VCCTL system and that their models can significantly reduce the scale of the experiment. For example, there are models that have been developed on the substitution of coarse cement particles by limestone fillers, slag, and calcium carbonate for the simulation of hydration and the development of strength (Bentz and Conway 2001).

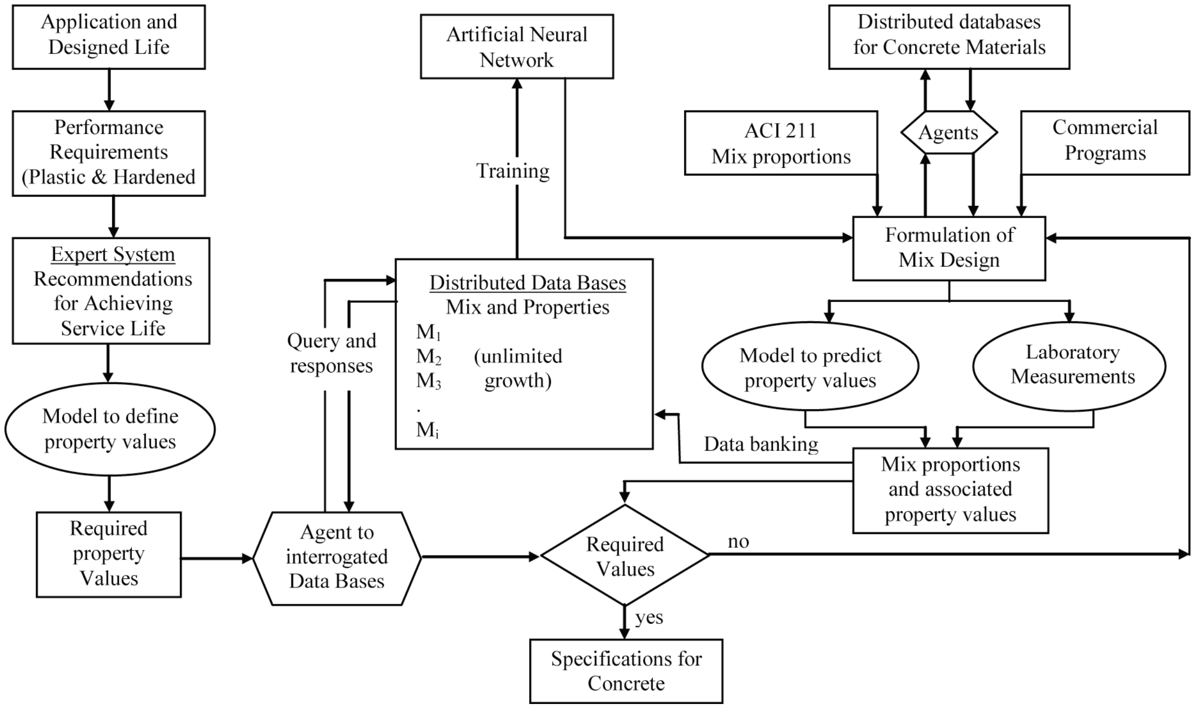


Fig. 7. Conceptual CIKS for designing HPC mixes (Clifton *et al*. 1997)

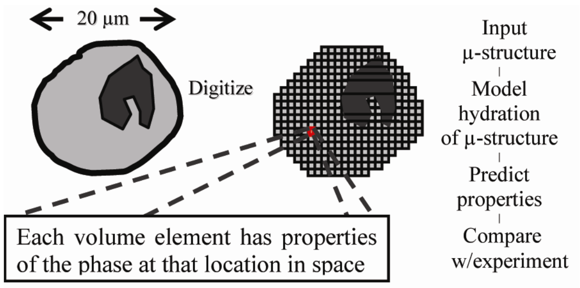


Fig. 8. Spatial resolution at the sub-particle level using small volume elements (1 μm cubes)

Other studies have described the prediction of physical properties of cement, modeling the influence of silica fume on diffusivity of cement pastes and concretes, and the influence of particle size distribution of cement on different properties of a high-performance concrete (Bentz *et al*. 2002; Bentz 2000; Bentz and Haecker 1999).

The models containing the VCCTL are continuously improved through collaboration between NIST and its partners such as the American Concrete Institute (ACI). The software VCCTL continues to develop and validate its predictive ability.

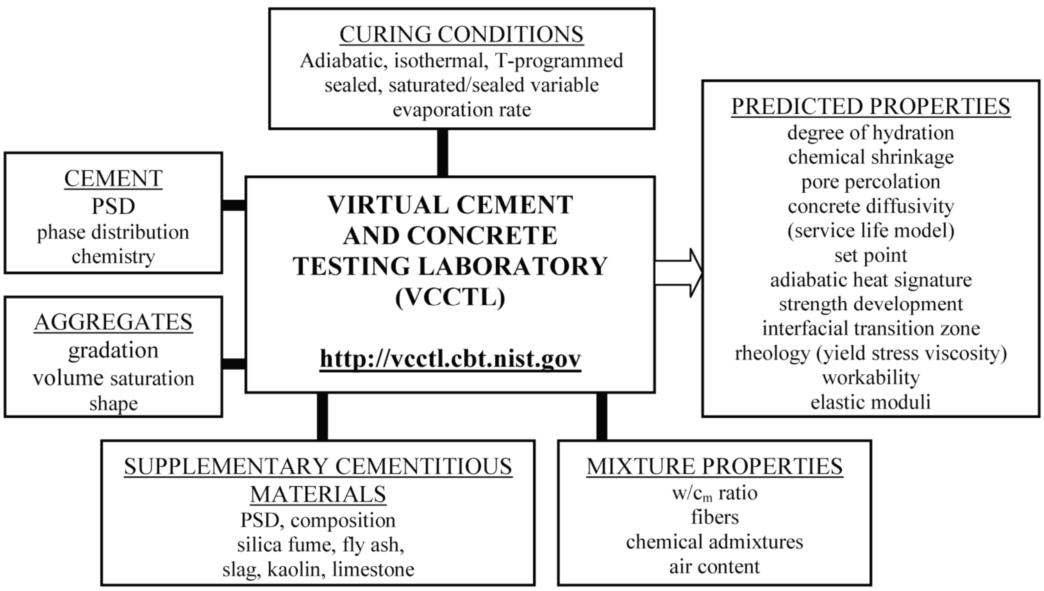


Fig. 9. Pictorial representation of the VCCTL software modules (Bullard *et al*. 2005)

8. Concrete mix design software

Concrete formulators are exposed to increasing pressure in terms of time and cost for the selection of concrete mix proportions conforming to specific requirements, notably in terms of consistency, strength and durability. These considerations have prompted several researchers to construct concrete mix design software based on different approaches. In the following, some software for the formulation of concrete are presented. Concrete Optimization Software Tool (COST) is a software for concrete mix optimization, which was developed by the Federal High Way Administration (FHWA) and NIST (Simon *et al.* 1997). It is a web-based system developed to help engineers, concrete producers and researchers to optimize their concrete mixes. COST is based on statistical models and methods of analysis and applies a Response Surfaces Methodology (RSM) to optimization problems of concrete mix proportions, where several input variables (components) influence a measured property (response) (Table 1).

Table 1. Example of components and responses

Components	Responses
1. Water 2. Cement 3. Mineral admixtures (fly ash, silica fume, slag, meta-kaolin) 4. Chemical admixtures (supper plasticizer, air entraining agent, …) 5. Aggregates	**Rheological Proprieties** (workability, air content, setting time, …) **Mechanical Properties** (compressive strength, elastic modulus, creep, …) **Durability** (freeze thaw, abrasion, carbonation, chloride diffusion, sulphate attack)

BétonlabPro in its current version (version 3), published in early 2008, is a software for the formulation of concrete (De Larrad and Sedran 2007). It was developed from the first version called Bétonlab launched in 1992 by the LCPC for educational purposes (De Larrad and Fau 1995). BétonlabPro is based on a new approach for the formulation of concrete (De Larrard and Sedran 1999). This approach relies primarily on an analysis of the structure of granular material based on stacking compressible model (Fig. 10). The software is equipped with a database in which the user can use and enrich by series of measurements on the components (gravel, sand, cement, minerals and chemicals admixtures).

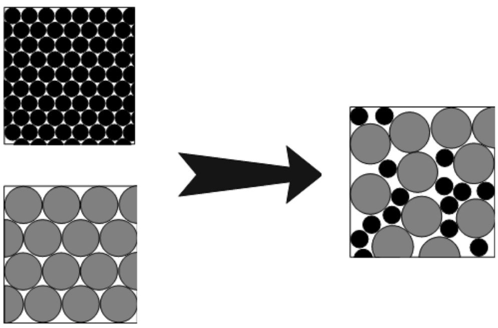


Fig. 10. Granular structure of the material (De Larrad and Sedran 1999)

Yeh (2007) developed a CAD for the optimization of concrete mixtures by using neural networks and technology of optimization. It has taken three steps for the development of this system. First, the problem of designing a concrete mixture is transformed into optimization formulation, including the objective function and constraint functions. Then the functions in the formulation, including strength and workability, are used to model a module based on neural networks. Finally, the optimization of formulation is solved by an optimization module based on nonlinear programming and genetic algorithms. These modules are integrated into a system of computer aided design. The architecture of the system is shown in Fig. 11.

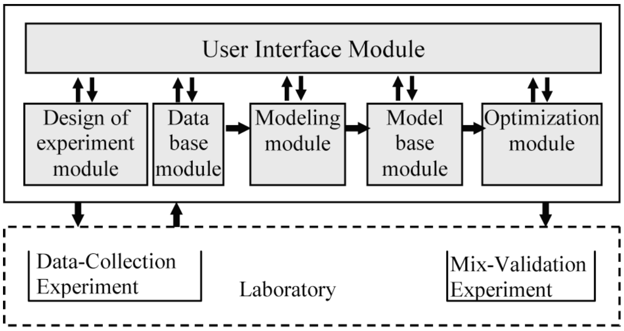


Fig. 11. CAD system architecture for optimization of concrete mix (Yeh 2007)

The system was evaluated and used to obtain a set of concrete mixtures with optimal ranges of workability (5–25 cm) and resistance to compression (25–55 MPa).

However, all these systems and software are valid for the specifications and standards inherent in some countries. In this context, the development of universally system is needed to cover the wide variety of concretes, particularly concrete with additives that preserve the environment and contribute to sustainable development. The development of such flexible system is under development by the authors (Boukhatem 2010).

The proposed system called SAICBA (in French: Système Automatisé Intégré de Connaissance pour les Bétons aux Ajouts) is an intelligent system to solve problems of predicting properties of concretes containing mineral additives such as slag, fly ash, silica fume and natural pozzolan. It also determines the efficiency of these additives in concrete to obtain the desired properties (slump, compressive strength). This system incorporates a computerized database, mathematical and neural network models (Fig. 12).

The system was validated by experimental tests. The system can predict the workability in terms of slump and the compressive strength of concrete containing additives and their efficiency factors. The main feature of this system is its flexibility that can significantly reduce the scale of the experiment and its ease of use by researchers with little computing experience.

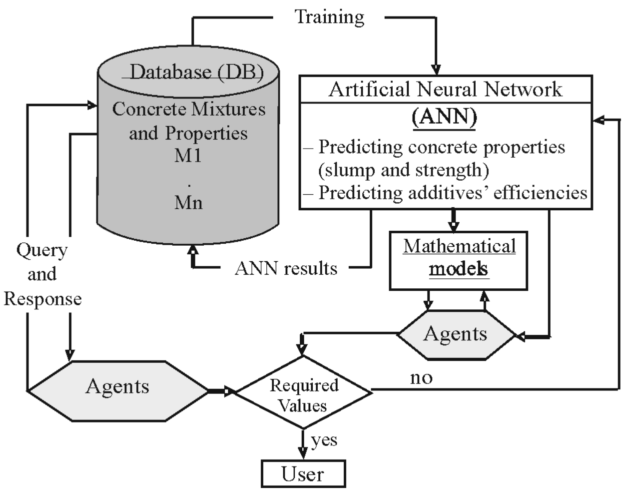


Fig. 12. Architecture of the SAICBA system (Boukhatem 2010)

9. Conclusions

Recent information technology developments had high impact on concrete technology. These techniques have facilitated sharing data among researchers and concrete practitioners. These techniques include simulation models, decision support and artificial intelligence systems that can be incorporated into integrated knowledge systems. Hence, a virtual laboratory which allows trial concrete mixing in a virtual environment and predicts its properties to achieve the required performance was developed. This idea concerns also the development of valid systems for specifications and standards intrinsic in some countries. In this context, the development of universally systems is needed to cover wide variety of concretes, particularly concrete with additives. However, it should be noted that these systems should still be validated by laboratory tests.

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NAUJŲ INFORMACINIŲ TECHNOLOGIJŲ NAUDOJIMAS RUOŠIANT BETONĄ. APŽVALGA

B. Boukhatem, S. Kenai, A. Tagnit-Hamou, M. Ghrici

S a n t r a u k a

Vystantis informacinėms technologijoms, atsiranda galimybių greitai gauti įvairiausios informacijos ir metodų, kaip modeliuoti sudėtingas sistemas. Pastaruoju metu paplito imitaciniai modeliai, duomenų bazės, sprendimų paramos sistemos ir dirbtinis intelektas. Šių metodikų pažanga statybų sektoriui ir toliau daro didžiulę įtaką. Šiame darbe siekiama pristatyti informacinių technologijų naujienas ir jų įtaką betono technologijoms. Apžvelgiami ankstesni tyrimai ir dirbtinio intelekto metodų taikymas ruošiant betoną. Be to, aptariamas integruotų kompiuterinių žinių sistemų vystymas, virtualių sistemų naudojimas ir programinė įranga betono mišiniams kurti. Per pastarąjį dešimtmetį šios sistemos padarė nemenką įtaką tam, kaip atliekamos inžinerinio projektavimo užduotys, ir turėtų paskatinti projektavimo užduočių perversmą ateityje. Jos – naudingi ir galingi įrankiai, leidžiantys spręsti sudėtingas problemas, tai mokslinis iššūkis betono technologijų srityje.

Reikšminiai žodžiai: informacinės technologijos, imitaciniai modeliai, dirbtinis intelektas, integruotos kompiuterinės žinių sistemos, virtuali sistema, betono mišinio sudėtis.

Bakhta BOUKHATEM. PhD student at the University of Blida, Algeria, where she also obtained her BS and Master degrees in civil engineering in 1999 and 2003, respectively. Her research interests include optimization using artificial neural networks.

Said KENAI. Professor at the Laboratory of Materials and Civil Engineering, University of Blida, Algeria. His research interests include cement replacement materials, durability of concrete, repair and rehabilitation of reinforced concrete structures.

Arezki TAGNIT-HAMOU. FACI, is a Professor at the Civil Engineering Department, University of Sherbrooke, Canada. He is a member of ACI Board Activity Committee on Sustainable Development, Committees 130, Sustainability of Concrete and 555, Concrete with Recycled Materials. His research interests include physico-chemistry and microstructure of cement and concrete, supplementary cementitious materials, and sustainable development.

Mohamed GHRICI. Associate Professor at the Civil Engineering Department, University of Chlef, Algeria. His research interests include concrete incorporating industrial by-products as supplementary cementitious materials, sustainable development, and durability of concrete.