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Survey on energy and comfort management in a building environment using advanced control systems engineering

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AB STR A C T
Given restrictions that comfort conditions in the interior of a building are satisfied, it becomes obvious that the problem of energy conservation is a multidimensional one. Scientists from a variety of fields have been working on this problem for a few decades now; however, essentially it remains an open issue. In the beginning of this article, we define the whole problem in which the topics are: energy, comfort and control. Next, we briefly present the conventional control systems in buildings and their advantages and disadvantage. We will also see how the development of intelligent control systems has improved the efficiency of control systems for the management of indoor environment including user preferences. This paper presents a survey exploring state of the art control systems in buildings. Attention will be focused on the design of agent-based intelligent control systems in building environments. In particular, this paper presents a multi-agent control system (MACS). This advanced control system is simulated using TRNSYS/MATLAB. The simulation results show that the MACS successfully manage the user's preferences for thermal and illuminance comfort, indoor air quality and energy conservation.

I. INTRODUCTION:PROBLEMSTATEMENT

1.1. Energy

The distribution of energy consumption in European house-holds in 1999 was as follows: 68% for space heating, 14% for waterheating and 13% for electric appliances and lighting. While thepercentage of space heating has decreased during the past 15years,thepercentageofconsumptionforthe operationofelectricalapplianceshasincreasedby10–13%;representingmorethanhalfof the consumed electricity. Operation of office equipment isresponsible for as much as 40% of the electricity consumed in anoffice building with the sector of office buildings and hence energyconsumed in these buildings growing in size (Intelligent EnergyExecutiveAgency(IEEA),http://www.iea.org).
Theconstructionsectorcoversoneeighthofthetotaleconomicactivity in the European Union (EU), employing more than eightmillion people. The intense activity in building construction, inconjunction with the need for energy savings and environmentalprotectionpolicy,dictateformorereasonabledesignpracticesforbuildings.ThenewlyreleasedEUDirective''EnergyPerformanceofBuildings'' (EPBD) concerns the use of energy in buildings andurgesmembernationsoftheEUtosetstricterregulationsregarding the efficient use of energy in buildings. For this reason,one of the main goals of advanced control systems, as applied tobuildings,istominimizeenergyconsumption.

1.2. Comfortconditions

Inthe1970sand1980s,theneedforenergysavingsresultedinthe design and construction of buildings that had small openings,lacked natural ventilation, etc. Because people spend more than80%oftheirlivesinbuildings,theenvironmentalcomfortinaworkplaceisstronglyrelatedtotheoccupants'satisfactionandproductivity. Ontheotherhand,aswellknown,energyconsump-tion is also strongly and directly related to the operation cost of abuilding. Hence, energy consumption and environmental comfortconditionsmostoftenareinconflictwithoneanother.
Inthepast20years,specialemphasishasbeengiventothebioclimaticarchitectureofbuildings.Bioclimaticarchitectureisgeared towards energy savings and comfort; utilizing glazing

andshadowingsystems,solarspaces,naturalventilation,thermalmass,Trombewalls,coolingsystemswithevaporationandradiation,etc. Bioclimaticarchitecturefocusesonthedesignandconstructionofbioclimaticbuildingsthattakeadvantageandmakeuseofsolarradiationandnaturalairflowfornaturalheatingandpassivecooling.Thequalityoflifeinbuildings(comfortconditions)isdeterminedbythreebasicfactors:Thermalcomfort,visualcomfort, and Indoor Air Quality (IAQ) [1–4]. Thermal comfort isdeterminedbytheindexPMV(PredictiveMeanVote)[2,4].PMViscalculatedbyFanger'sequation[4,5].PMVpredictsthemeanthermal sensation vote on a standard scale for a large group ofpersons. The American Society of Heating Refrigerating and AirConditioningEngineers(ASHRAE)developedthethermalcomfort indexbyusingcoding—3forcold,—2forcool,—1forslightlycool,0 for natural, +1 for slightly warm, +2 for warm, and +3 for hot. PMVhasbeenadoptedbytheISO7730standard[6].TheISOrecommends maintaining PMV at level 0 with a tolerance of 0.5as the best thermal comfort. Visual comfort is determined by theillumination level (measured in lux) and by the glare that comesfromdirectviewingofthesolardisk.

Indoorairqualitycanbeindicatedbythecarbondioxide(CO_2)concentration in a building [1,3]. The CO_2 concentration comesfrom the presence of the inhabitands in the building and fromvarious other sources of pollution (NOx, Total Volatile OrganicCompounds (TVOC), respirable particles, etc). Ventilation is animportantmeansforcontrollingindoor-airquality(IAQ)inbuildings.Supplyingfreshoutdoor-airandremovingairpollutantsandodoursfro minteriorspacesisnecessaryformaintainingacceptableIAQlevels.However,ventilationratesinsidebuildingsmustbeseriouslyreducedinordertocontrolthecoolingorthermal load in an improved manner and reduce the energy load.In many cases though, this contributes to a degradation of theindoor-airqualityandtowhatisgenerallyknownas'sickbuildingsyndrome'(SBS)[7].Forthesereasons,IAQisnowamajorconcerninbuildingdesign.Demand-controlledventilation(DCV)systemsofferanefficientsolutionfortheoptimizationofenergyconsump-tionand indoor-air quality[8].

The main characteristic of DCV systems is that ventilation ratesare modified according to the value of a certain parameter, forexample the CO_2 concentration, which is representative of thepollutantloadinaroom.Thistechniquehas alreadybeensuccessfully applied in many cases by using mechanical ventila-tion. Dounis et al. [9] investigated the potential application of CO_2-based DCV to control ventilation rates for a building with naturalventilation. Simulations were performed in which window open-ingswereadjustedbasedonmeasuredCO_2concentrations.Duetoconcernsovertheconstant variationofnaturalventilationdrivingforces, fuzzylogicwasusedinsteadofconventionalon–offorPIDcontrol.Carbondioxideconcentrations,windowopenings,andairtemperatures are presented for a simulated day. The feasibility ofsuchasystemwasdemonstrated. Wangetal.[10]developedarobustcontrolstrategytoovercomethecontroldifficultieswhen DCVcontroliscombinedwitheconomizercontrol.Themaindifficultyistheemergenceinstabilityphenomena(alternationandoscillation) inthetransitionphase between different control modes. Wang et al. [11] developed anoptimalandrobustcontrolofoutdoorventilationairflowrate.Thisstrategy employs a dynamic algorithm to estimate the number ofoccupants in the indoor building based on the CO_2 measurement.Theoptimalrobustcontrolstrategyachievesindoorairqualityandminimum energy consumption. Hence, the second main goal andcharacteristic of advanced control systems is the achievement ofoccupants'comfortconditions.

1.3. Controlobjective

Livingspaceclimateregulationisamultivariateproblemhaving no unique solution, particularly in solar buildings. Morespecifically, the goals of an intelligent management system forenergyandcomfortareasfollows:

- High comfort level: Learn the comfort zone from the user'spreference, and guarantee a high comfort level (thermal, airqualityandilluminance)andgooddynamic performance.

- Energysavings:Combinethecomfort conditionscontrolwithan energysavingstrategy.
- Airqualitycontrol:ProvideCO_2-baseddemand-controlledventilation(DCV)systems.

Satisfaction of the above requirements demands control of thefollowingactuators/effectors:

- Shadingsystems,tocontrolincoming solarradiationandnaturallight,aswellastoreduceglare.
- Windowsopeningfornaturalventilationormechanicalventila-tion systems, to regulate natural airflow and indoor air change,thusaffectingthermalcomfortandindoorairquality.
- Electriclightingsystems.
- Auxiliaryheating/coolingsystems.

User interactions always have a direct effect on the systemunderconsiderationinorderto givetheuserthefeelingthat heorshe controls his or her own environment. Users of an electriclighting system may switch the lights on or off, or may preciselychoose the electric lighting level. Heating system users may changethetemperaturesetpoint.Anincreaseofthesetpointwillimmediatelystarttheheating systemasfarastheindoortemperatureisbelow thissetpoint.Moreover,peopleusingblindsmaychooseanyblindpositiontheydesire.

The combined control process for the above systems requiresoptimal performance of almost every subsystem, under the basicassumptionthateachoperatesnormallyinordertoavoidconflictsarising between users' preferences and the simultaneous opera-tions of these control subsystems. Mathews et al. [12] developedcost efficient control strategies to achieve optimal energy andacceptablecomfortconditions.

We could obtain optimal operation of the local controllers byusingindividualswhoareexpertoperatorsofthesystem,however,thisisimpossible.Therefore,weneedtodesignthearchitectureofamulti-agentcontrolsystemthatwillincorporatetheknowledgeofsuchexpertoperators.Suchasystemincludesanintelligentsupervisor to coordinate the operation of the partial sub-systems,whicharethelocalintelligentcontrollers–agents.Inamulti-agentcontrolsystemofabuildingmicroclimate, highprioritymaybegivento passive heating/cooling techniques; aiming at maximization ofenergyconservationwhileincorporatingtheusers'preferences.

A basic characteristic of the advanced control systems is theirabilitytooperatewithsymboliclanguage andnon-exactandfuzzylogic that humans perceive better. It is done in conjunction withComputationalIntelligence.Techniques ofthiskindhavebeen widely applied in the industry all over the world in hundreds ofpower plants. However, in complicated systems, mathematicalmodeling can hardly describe a real system in real time. For thisreason, Computational Intelligence techniques, like Fuzzy Logic(humanapproximateclassificationand reasoning),NeuralNetworks (the neurophysiology of the human brain), and GeneticAlgorithms (Darwinian evolutionary laws) have been used to solveproblemsthatarisefromthemanagementofsuchsystems.

Thedifferentapproachestocontrolsystemsforindoorbuildingenvironments can be roughly classified into the following cate-gories: (i) conventional methods; (ii) computational Intelligencetechniques;and(iii)agent-basedintelligentcontrolsystems.However,itshouldbenotedthattheoverlappingbetweencategoriesisunavoidable.Forexample,genetic algorithmscantuneafuzzycontroller,oracontrolleragentcanbedevelopedbyfuzzylogic.Thenumberofpublicationsonthesubjectofcontrolsystemsforbuildingcontrolisquitelarge.Thisbeingso,onlyasmallportionofthesearelistedinthereferences.Becauseitisbeyondthescope ofthis survey paper to cover all of these studies in detail, we willinstead,presentanoverviewofthesecategoriesinthenextsectionsandfocusonmulti-agentcontrolsystemsinmoredetail.Therefore,themainobjectiveofthispaperistosurveystateoftheartcontrolsystems in buildings and in particular, the multi agent controlsystems thathavebeenrecentlydeveloped.

II. CONVENTIONAL CONTROL SYSTEMS ENGINEERING IN BUILDINGS—AN OVER VIEW

1.4. Classicalcontrollers

Originally, the goal of the development of control systems forbuildingswasmainlyminimizationofenergyconsumption.Thermostatswereusedforthefeedbackcontrolofthetemperature[13].Inordertoavoidfrequentchangesbetweenthetwostatesofathermostat, thermostats with a dead zone were introduced andused. This kind of control is called bang–bang control with deadzone.However,overshootsinthecontrolledtemperaturewerenotavoided,whichresultedinanincreaseinenergyconsumption.Inordertosolvetheproblem,designersusedProportional–Integrate–Derivative (PID) controllers [13,14]. Although thesecontrollersimprovedthesituation,improperchoiceofthegainsinthePIDcontrollercouldmakethewholesystemunstable.Therefore, designers resorted to optimal, predictive, or adaptivecontroltechniques.

1.5. Optimal,predictive,andadaptivecontrol

Important research was conducted on optimum and predictivecontrolstrategiesduringthe1980sand1990s.However,noindustrialdevelopmenthasfollowedthesescientificstudies,especially due to implementation issues. In order to use optimalcontrol [15–24], or adaptive control, [25] a model of the building isnecessary.Predictivecontrol[26,22,27–29]isveryimportantbecause it includes a model for future disturbances (e.g. solar gains,presenceofhumans,etc.).Itimprovesthermalcomfortmainlybyreducing overheating [30–32] but especially through night cooling.However, mathematical analysis of the thermal behavior of abuilding generally results in non linear models and even moreimportantly,thesemodelsdifferfromonebuildingtoanother.
Adaptivecontrollershavetheabilitytoself-regulateandadapttothe climate conditions in the various buildings. More specifically,adaptive fuzzy controllers are regarded as the most promisingadaptivecontrolsystemsforbuildings[16,30,25].Anotherwaytosolvetheproblemisbyusingparameterestimationmethods(RecursiveLeast-Squaresestimation).Nesler[33]developed adaptive control of thermal processes in buildings. The standard PIcontrol algorithm is adequate for the control of heating, ventilating,andair-conditioning(HVAC)processes.TheRLSestimatorprovidesestimatesof thegain,timeconstantand dead timeof a process.RLS estimator diverges when the control loop is subjected to anunmodeled load disturbance. Actuator nonlinearity is also a well-knownlimitationofself-tuningcontrollers.Onlyafewauthorshavedirectly applied adaptive techniques that learn the characteristics ofabuildinganditsenvironment[33,34].
Because the above optimal solutions are not always feasible,solutionsthatareapproximatetotheoptimalonehavebeenused.However, such techniques suffer from various drawbacks, some ofwhichare:

- Theneedforamodelofthebuilding.
- The use of elements of bioclimatic architecture complicates theprocessofminimizationofthecostfunctionandifsucha minimizationisobtained,theresultsarenotapplicableinpractice.
- The need to make parameter estimation in real time with thealgorithmsbeingusedsensitivetonoise.Thus,underrealconditions,suchtechniquesmaygiveerroneousresults.
- Suchtechniquesdonotdealwiththeproblemofcomfort.Nonlinearfeaturesthatcoulddeterminesomedifficultieswhen monitoringandcontrollingHVACequipmentcharacterize thePMVindex.
- Theresultingcontrolsystemsarenotuserfriendly,sincetheuser doesnotparticipateintheconfigurationoftheclimateofhis/herenvironment(Userpreferences).
- Thesecontrolmethodsarenotuselearningmethods.
- Theclassicalcontrolmaximizestheenergyconservationwithout givingprioritytopassivetechniques.

III. COMPUTATIONAL INTELLIGENCE IN BUILDINGS

Application of intelligent methods to the control systems ofbuildings essentially started in the decade of the 1990s. ArtificialIntelligence (AI) techniques were applied to the control of bothconventional and bioclimatic buildings. Intelligent controllers,optimized by the use of evolutionary algorithms were developedfor the control of the subsystems of an intelligent building [35]. Thesynergy of the neural networks technology, with fuzzy logic, andevolutionary algorithms resulted in the so-called ComputationalIntelligence(CI),whichnowhasstartedtobeappliedinbuildings.To overcome the nonlinear feature of PMV calculation, time delay,and system uncertainty, some advanced control algorithms haveincorporatedfuzzyadaptivecontrol[36–39],optimalcomfortcontrol[18],andminimum-powercomfortcontrol[40].Akindofdirect neural network controller, based on a back-propagationalgorithm,hasbeendesignedand successfullyappliedinhydronicheatingsystems[41].

Neural networks have been extensively used in Japan [42]where they have been applied to commercial products such as airconditioners, electric fans etc. A system of two neural networks hasbeen incorporated in an air conditioner to further fine-tune theequipmenttotheusers'preferences.Oneof thetwoneuralnetworks estimates the value of the PMV index by using sensorinputs only. However, this is not always optimal for a given user.Theotherneuralnetworkfurthercorrects thisoutput.Theusercantrainthisneuralnetwork.

1.6. Fuzzysystemsandevolutionarycomputation

The need to obtain energy savings and to guarantee comfortconditions,takingintoconsiderationtheusers'preferences,droveresearcherstodevelopintelligentsystemsforenergymanagement inbuildings(BuildingIntelligentEnergyManagementSystems—BIEMS), mainly for large buildings like office buildings, hotels,publicandcommercialbuildings,etc.Thesesystemsaredesignedtomonitorandcontroltheenvironmentalparametersofthebuilding's microclimate and to minimize the energy consumptionand operational costs. A large number of publications regarding theapplication of fuzzy techniques on BIEMS can be found in thereferences. The results cited are superior when compared to thoseofclassicalcontrolsystems.Recently,thepracticalapplicationsoffuzzyandneuralcontrolforHeatingVentilationandAirConditioning(HVAC)systemshavebeendiscussedwith thegoalbeingperformanceimprovementoverclassicalcontrol[43–47].

Therequirementforamathematicalmodeloftheoperationofabuilding has been an obstacle to the application of traditionalcontrol methods in buildings. In intelligent systems, namely inmodel-freecontrollers,suchamodelisnotrequired.Thisfactisageneralinnovationinthedevelopmentofautomaticcontrolsystems. By incorporating new-type, higher-level variables thatdefine comfort into the intelligent controllers (e.g. PMV [48]), itwas possible to control comfort without going into the regulationof lower level variables like temperature, humidity and air speed.Insuchsystems,usersstarttoparticipateinthespecificationofthedesiredcomfort.

Genetic Algorithms and methods coming from the theory ofadaptive control are used to optimize fuzzy controllers. Fuzzy logiccontrol has been used in a new generation of furnace controllersthat apply adaptive heating control in order to maximize bothenergy efficiency and comfort in a private home heating system[49]. The development of fuzzy controllers to control thermalcomfort,visualcomfort,andnaturalventilation,withthecombinedcontroloftheses ubsystemshasledtoremarkableresults[50,37,17,51,36,48,52–72,39].

1.7. Synergisticneuro-fuzzytechniques

Neuro-fuzzy systems originated when neural network techni-ques were used in fuzzy technology. Hybrid systems like ANFIS(Adaptive Neuro-Fuzzy Inference System) [73] have been used forpredictionandcontroloftheartificiallightinginbuildings,following variations of the natural lighting [74]. Proper choice ofthepredictivecontrolstrategy,combinedwithanon-linearmodeling of the building, the user's behavior, and the predictionof the climate parameters allowed NEUROBT system to obtainenergy savings and to guarantee satisfactory comfort [27]. A neuralcontroller, equipped with the prediction capabilities of neuralnetworks, can be used in the control of hydronic heating systemsand solar buildings [75–77,32]. Kanarachos and Geramanis[41]haveproposedanAdaptiveNeuralNetwork(ANN)controllerforthe control of single zone hydronic heating systems. The inputsand outputs of this controller involve parameters related to theheating plant and the indoor set point temperature. However, noforecasting ofeither weatherparameters orindoor conditionsweremade.

Thetechnologyofneuralnetworkshasfoundi mportantapplications not only to the control systems of buildings [78–81,57,46] but also to more general problems regarding renewableenergy sources. Neuro-fuzzy systems havealso been studied.Egilegor et al. [57] developed and tested a fuzzy-PI controlleradaptedbyaneuralnetwork.Howe ver,itdidnotofferspectacularimprovement.

Yamada et al. [82] developed an air-conditioningcontrol algorithm that combines neural networks, fuzzy systems,and predictive control. This system predicts weather parametersand the number of occupants. These predictions are then used toestimate building performance in order to achieve energy savingsandtomaintaintheindoorconditionsi nahighcomfortlevel.

1.8. Designoffuzzylogicandneuralnetworkc ontrollers

1.8.1. FuzzyPcontrollers

Manydifferentmethodsexisttousefu zzylogicinclosed-loopcontrol. The simplest structure is to use the measurement signalsfromtheprocessastheinputstothefuzz ylogiccontrollerandtheoutputs of the fuzzy logic controller to drive the actuators of theprocess.Thispurefuzzylogicsystemiscall edfuzzyPcontroller.TheinputsofafuzzyPco ntrollerarePMVandoutdoortemperature.Au xiliaryheating(AH),auxiliarycooling(AC),a ndventilationwindowopeningangle(AW)set tingsarethecontrolleroutputs [36,52]. These outputs, which are deterministic signals,drivetheprocessactuators.

A global P controller has six inputs (PMV, ambient temperatureT_{amb}, CO_2 concentration, change of CO_2 concentration, DaylightGlare Index (DGI), and illuminance (ILL)), and four outputs (AH/AC,SHaDowing, Artificial Lighting, and window opening angle (AW))[39,65].Triangularandtrapezoidalme mbershipfunctionsareusedtocovertheinput–outputuniverseofdiscourse.Intheruledesign, priority is given to passive techniques to obtain indoor comfort.During moderate seasons, the fuzzy rules allow natural coolingthrough window openings in order to reach thermal comfort byusingnaturalventilation.Duringwinterand summer,windowsarekeptclosedtoavoidther mallosses.Thesolargainsarecontrolledto allow passive heating during the winter and cut off excessiveheatingduringthesummer.

Indoor illuminance fuzzy rules are designed to give priority tothenaturallighting.Theelectriclightingiso nwhenindoorilluminanceiszero,i.e.duringni ghttimeandduringcloudyconditions. When indoor illuminance is increased, the electriclightingisimmediatelyturnedoffands hadingregulatestheindoorvisual comfort. The performance index in the building controlsystemisminimizationofenergycons umption[67].

1.8.2. PI-likefuzzylogiccontrollers

FuzzyPIDcontrollersareclassifiedin totwomajorcategories,according to their structure [83,84]. The first category of fuzzy PIDcontrollers involves typical fuzzy logic controllers (FLCs) realizedasasetofheuristiccontrolrules.Inord ertobeconsistentwiththenomenclature [85] and to distinguish from the second category offuzzy PID controllers, we will call FLCs in this category PID-like (PI-likeorPD-like)FLCs.Mostoftheresearchonfuzzylogic controldesignreferstothiscategory[86–90]. The second category of fuzzy PID controllers is composed of theconventional PID controllers in conjunction with a set of fuzzyrulesandafuzzyreasoningmechanismt otunethePIDgainsonline[91]. Controllers of this type can adapt to varying environments.Themaindisadvantageofacon trolsystemofthiscategoryisthatitis mainly model-dependent, since it requires human experiencewith controlling the plant in order to define the range of theproportionalgain.

Inmostcases,thefuzzyPIcontrollerisanincre mentalcontroller.The conventional fuzzy PI controller is described by the equationu(k +1)=u(k)+Du(k)(Fig.1)where kisthesamplinginstanceand Du(k)istheincrementalchangeincontrollero utputdeterminedby

fuzzy rules. PI-type FLCs most commonly are followed by PD-typeFLCs.Inaproportional–integral(PI)controller,proportional(P)andinte gral(I)actionsarecombinedtotakeadvantage oftheinherentstability of the proportional controllers and the offset eliminationability of the integral controllers. PD-type FLCs are suitable for alimitedclassofsystems.Theyarenotsuitable whenmeasurementnoiseandsuddenloaddisturbancesexist.PID-typeFLCsarerarelyusedbecauseofthedifficultiesassociatedwiththegenerationofanefficient rule base and the need for tuning its large number ofparameters. Itisnaturaltouseanincrementalcontrollerwhen,forexample,the actuator is a motor or a valve. It is an advantage that thecontrolleroutputisdrivendirectlyfromanintegrator,becauseitiseasy to deal with wind up and noise. The fuzzy PI controller uses asinputstheerrorsignalanditschange(Fig.1). The advantage of a fuzzy PI controller is that it does not have anoperatingpoint.Thecontrolstrategyofrulesevaluatesthedifferencebetween themeasuredvalueandtheset point andalso evaluates the change of this difference in order to decidewhether to increment or decrement the control variables of thebuilding. A fuzzy logic controller can implement nonlinear controlstrategies. If comfort condition (PMV) is 'cold', the increment willbestrong,regardlessofitstendency,butifthePMVerrorissmall,thetendencyistakenintoaccount.Table1showstherulebaseofaPIcontrollerinatableformat.

1.8.3. AcombinationofFLC,neuralcontroller,andPIDcontroller

Intheilluminancecontroller,acascadecontrolstrategyisused[71]. This strategy contains a main illuminance fuzzy controllerand a PID controller as an auxiliary controller. The illuminanceprocess is in close dependency with the external solar radiationchanges,whichcanbeveryunpredictableoroscillatory.Withtheuse of the cascade control strategy, which is complement to thefeedback control, the performance of the corrective action of therollerblindisimproved.Themainfuzzycontrollerdeterminestheproper position of the roller blind in order to maintain the insideilluminance at the desired value. The auxiliary PID controllermanipulatesthesignalforproperalternationoftherollerblind,tonullifytheerrorbetweenthecurrentandthedesiredposition.Twofilters, realized in filter blocks, are included to smooth possible fastand frequent movements of the roller blind, that happen whenexternalsolarradiationchangesoccurfrequently.Propersettingofthe filter time constants results in smoother roller blind alterna-tions. We want to avoid excessive movements of the roller blind,forthesimplefactthatitisannoyingtothe occupants.Curtisetal. [25] developed a neural controller that gradually undertakes thecontrolofHVACprocessesfromaPIDcontroller.In[92]Curtisand

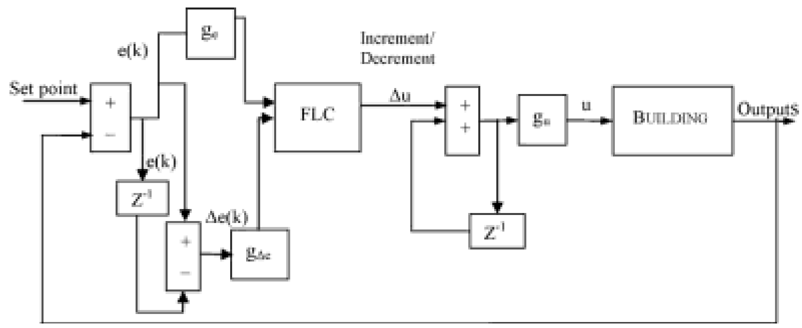

Fig.1.StructureoffuzzyPIcontroller.

Table1
TherulebaseofafuzzyPIcontroller[85].

De	e					
NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS
	ZENM	NB	NM	NM	NM	NS
	ZE	PSNS	NB	NM	NS	NS
	ZE	PS	PMZE	NB	NM	NS
	ZE	PS	PM	PBPS	NM	NS
	ZE	PS		PSPM		PBPM
NS		ZE		PS		PM
PMPM		PBPBZE		PS		PSPM
PB	PBPB					

Shavit a neural controller was used to augment the output of a PIcontroller. This controller attempts to modify the output of a PIcontroller in a way that the motion of the actuator is minimized.Sucha combinationissuitable fornon-linear HVACsystems.

1.8.4. AdaptivefuzzyPDandfuzzyPIDcontroller

ThestructureoftheadaptivefuzzyPD controlleristhesameasforthefuzzyPDcontroller.ThedifferenceisthattheadaptivefuzzyPDcontrollerusesasecond-ordersystemasareferencemodelforthe determination of the scaling factors of the controller.
TheobjectiveistodesignanadaptivefuzzyPD controllersuchthatthebehaviorofthecontrolledbuildingremainsclosetothebehaviorofa desired model. The adaptive fuzzy PD controller is based onscaling factors $g_e$and $g_{De}$and g_u(Fig. 1) in order to improve thesystem'sresponse[39].
Calvino et al. [37] add an adaptive network to the model inorder to improve some general characteristics of a classical PIDregulationsystem.Furthermore,theymodifiedsomecontrolrules,aimingatdeterminingamonotone''controlsurface''toguaranteebetter stability features of the system [93]. The addition of theadaptivenetworktotheoriginalmodelallowsustovarythevaluesof the parameters regarding the integrative and derivative blocks:so doing, these parameters will depend on the peak of the ''stepresponse'',whichimprovesthestability oftheentiresystem.

1.8.5. Neuralnetworkcontrollers

In thermal comfort control [46] and in the temperature controlofhydronicheatingsystems[41],directneuralnetworkcontrollers(NNC)areused.Thesecontrollersarepracticalandcontrarytotheindirectneuralnetworkcontrollers,theydonotrequiretheidentification model of the plant. Fig. 2 shows the structure of atwo-layer multi-input and single-output (MISO) neural networkcontroller [46]. The controller has two inputs and one output: e istheerrorbetweenPMVsetvalueandfeedbackvalue,ėistheerrorderivative,anduisthecontrolsignaltothebuilding.
Theequationsofneuralnetworkcontrollerare

$y¼w_{11}eþw_{12}\dot{e}þw_{13}b$

$$Þ¼\frac{1}{1þexpð—y^2Þ}$$

whereyistheinputtotheoutputlayerofNN;w_{11}andw_{12}arethesynaptic weights; w_{13} is the synaptic weight of the fixed input(bias)b = 1;w(y)istheactivationfunction(unipolarsigmoidfunction);uistheoutputintheoutputlayer;andh*isthelearning-rate parameter. Training of a neural network is essentially theregulationofitsweightcoefficientsinaway thatminimizesacost function.Thedeterminationoftheweightsoftheinterconnectionsbetween the neurons is based on the gradient descent algorithm.At the beginning, the algorithm assigns random values to theweightsofthenetwork.Thetwosignalsattheinputofthecontrollerareobtainedandtheoutputuofthecontrolleriscomputed.Next,thealgorithmupdatestheweightsofthenetwork,as well as the new output signal u, which is then supplied to thebuilding.

1.9. Tuningoffuzzylogiccontrollers

It is important to distinguish

between the problems of tuningand of learning in an FLC. Tuning is mainly concerned with theoptimization of an existing FLC, whereas learning constitutes anautomated design method for fuzzy rule sets. Tuning processesassume a predefined rule base and their goal is to find a set ofoptimalparametersforthemembershipfunctionsorforthescalingfactors(normalizedgains).Thesegainsareusedtomapthe actual inputs and outputs of the FLC on the normalized universe ofdiscourse [—1, +1]. Learning processes perform a more elaboratetaskwhilesearchinginthespaceofpossiblerulebasesanddo not depend on a predefined set of rules. The most importantoptimizationtechniquesare:

1. Tuning of the scaling factors for the control inputs and outputsthatcanbeachievedbyasetofmeta-fuzzyrules.Thisapproachhas a trial and error nature. A good example can be found in[94,95,47].
2. Parameterizedcontrolparameters(scalingfactorsandmember-shipfunctions)adaptedbyGeneticAlgorithmstoafitnessfunction that specifies the design criterion in a quantitativemanner[96].
3. A formal approach to the derivation of the scaling factors, aimingat establishing an analytical relationship between the values ofthescalingfactorsandtheclosedloopbehaviorofthecontrolledprocess[85].
4. Theinputandoutputuniverseofdiscourseofthe FLCisnormalized on the range [—1, +1]. The gains are chosen asboundsontheinputsandoutputsofthecontroller(trialand error)sothattherulebaserepresentstheactiveregiononthecontrolactions:

$e^{g¼} \frac{1}{\max(e)}; \; \dot{D}e^{¼} \frac{1}{\max(\dot{D}e)}; \; g^{¼} \frac{1}{\max(u)} \; u$

5. Thechoiceofgainsisdonewithanon-lineauto-tuningstrategy

$Dw¼—h \frac{@E}{@w_{ij}} ¼—h \cdot \frac{@E}{@PMV} \cdot \frac{@PMV}{@u} \cdot \frac{@u}{@w_{ij}} ¼ h^{0} \cdot \frac{@PMV}{@u} \cdot \frac{@u}{@w_{ij}}$

[97].Letthemaximumvaluesofthetwofuzzycontrollerinputs duringthelast$T_A$secondsbe$\max_{T_A}\{e(kT)\}$and$\max_{T_A}\{De(kT)\}$.
Wedefinethemaximumgainvaluesas

$g_e ¼ \frac{1}{\max_{T_A}(e)}; \quad g_{De} ¼ \frac{1}{\max_{T_A}(De)}$

1.10. Optimizationoffuzzylogiccontrollers

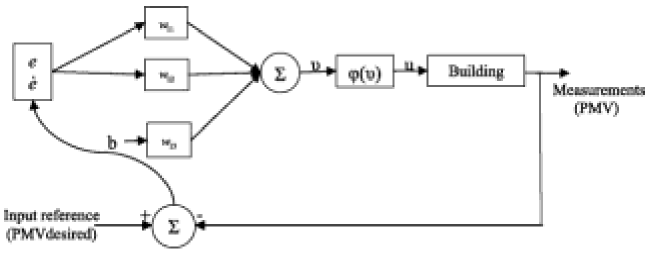

Fig.2.Adirectneuralnetworkcontroller.

The gradient-based optimization technique determines searchdirectionsforminimizationofanobjective(ororerror)function.Wecanusethistechniquetominimizeenergyconsumptionindistributedenvironmentalcontrol systems without increasingtheoccupants'thermaldissatisfaction[98]. There are several such derivative-free techniques, the mostpopularofwhichare:GeneticAlgorithms(GAs),simulatedannealing, random search and downhill simplex method. GAsare adaptive search and optimization algorithms that work bymimicking the principles of natural genetics [99]. These algorithmsare,however,verydifferentfromtraditionalsearchandoptimiza-tionmethodsthatareusedinengineeringdesignproblems.Fundamentalideasareborrowedfromgeneticsandareusedartificiallytoconstructsearchalgorithmsthatarerobustandrequireminimalproblemrelatedinformation.
Dounisetal.[51]developedaGAs-basedoptimizationtechnique for fuzzy controller for thermal and indoor air qualityin buildings. Kolokotsa et al. [66] have proposed an optimizationstrategythatintegratesinaGeneticAlgorithmtheindoorcomfortrequirements with the energy consumption, targeting to satisfythe indoor comfort requirements and simultaneously minimizethe energy consumption. The solution of the Genetic Algorithmprovidestheoptimalindoorcomfortsettingsthatarethenfedintothecontrolleras newsetpoints.
In [62] the objective was to develop and test user adaptivecontrollersforblinds,electriclightingandheating.Forthispurpose,anintegratedcontrolsystemthatadaptstothecharacteristicsoftheenvironmentandthebuildingwasdevelopedand successfully implemented. The system was built on threenestedcontrollevels:level1wherethesystemtranslatesphysicalvalues into actuator commands; level 2 where the fuzzy logiccontrollersareimplemented;andlevel3 whereadaptationaspectsare dealt with. User adaptation was performed by means of GAsthat optimize the parameters of the fuzzy logic controllers. GAshave shown to be the most efficient optimization method for thistask. An important result cited in the paper is that because theautomaticcontrolsystemdidnotsatisfyuserdesires,theyrejectedit at a high percentage rate (25%), compared to the user adaptivesystem.
Alcalaetal.[100]usedGAstodevelopsmartlytunedfuzzylogiccontrollers for heating, ventilation, and air conditioning systems,takingintoaccountenergyperformanceandindoorcomfortrequirements. Also, Lam [101,29] proposed a classifier system withGAs in on-line control for an air conditioning system. The target ofthiscontrolsystemistomaketheairconditioningcontrolleraself-learningcontrolsystem.

1.11. Supervisorycontrol

Optimalcontrolaimstopreserveindoorenvironmentalconditionswithminimalenergyexpenditureunderdynamicoutdoor and indoor conditions. It can be achieved by using localcontrollers of the sub-systems and optimal supervisory control ofthebuilding.Fortheadvancedcontrolsystemsinbuildings,supervisory control is an interesting subject. The set-points areresetbythecontrollersupervisorduetothechangesoftheoutdoor/indoorloads,theuserspreferences,andtheenergyconsumption.Kolokotsaetal.[66]developedoptimizationtechniquesbasedonGeneticAlgorithmstargetedatoptimalindoorcomfortsettings.Thesenewsettingsaredirectlyappliedtothe controllers. Wang et al. [19] developed an on-line controlstrategy for an air-conditioning system using digital control forVAV (variable air volume) AHUs (air handling units). A geneticalgorithm is used to detect the optimal settings of the controllers.This strategy predicts the system response to the changes of thecontrol set-points using on-line parameter identification and self-tuning. Dounis et al. [55] developed an intelligent coordinator offuzzycontrollers–agentsforindoorenvironmentcontrolinbuildings using 3D fuzzy comfort set. In this system, the basicfactorsthatparticipateinthecontrolofindoorenvironmental conditionsarethecontrollersandtheusers'comfortrequirements.Synchronization of the control system is obtained by the designandimplementationofanintelligentcoordinator,whichisacentralizedone.Itconsistsofamasteragentandaslaveagentthatare both implemented by fuzzy logic theory. The master agentevaluates the energy efficiency of the building and comfort ofoccupants. A fuzzy inference mechanism produces signals thatactivatetheslaveagentandchangethesetpointsofthecontrollers.Theslaveagentisafuzzynegotiationmachine(FNM), which synchronizes the interaction of the fuzzy controllersandmanagestoavoidconflictsbetweenthem.Whensomeconditionsdeterminedbytheslaveagentaresatisfied,fuzzycontrollersareactivated,otherwisetheystayinactive.

1.12. Userinterfaces

Insmartbuildings,thebuildingautomationsystemsandcontrol networks (BACnet) [102] provide user interface devices(thermostat,valves,keypads)sothattheusercaninteractwiththecomponentsofeachfunction(heating,cooling,ventilation,shading,security).Thesystemallowsusersbysettingtheirpreferences(desiredcomfortconditions,energymanagement,andoccupancyschedule).

Kolokotsaetal.[103]usesasmartcardunit(kiosk),manufactured by the French company INGENICO that performstheinterfacebetweenthesystemand theuser.Theusers'preferences are monitored via the smart card unit. Consideringthe users' preferences collected from the smart card unit for aspecifictime,suchasoneweek,astatisticalanalysisisperformedevaluating the average users' preferences corresponding to thethree indoor comfort controlled variables: PMV index, indoorilluminanceandCO_2concentration.

Keyson et al. [104] proposes a mixed-initiative user interfacethatisanintelligentthermostatthatcanreduceenergyconsumption. An embedded statistical model uses living patternstoinferuserintentions.

In practice, however, fully usable user interface systems areundefinedandunrealized[105]formanyreasons.Auserinterfacedevice is difficult to use in different buildings. Each building hasdifferent equipment, control systems and requirements. Even inbuildings with the same systems, the environment within whichtheyoperatecannotbeforeseen.

Penner and Steinmetz [105] developed a Dynamic InterfaceGenerationforBuildingEnvironments(DIGBE)thatdynamicallyadaptstotheuseranddataenvironments.

ThementionedcontrolsystemsarelistedinTable2.Wesummarizethemostimportanttechnicalissuesregardingtheclassical and advanced control methods. In the column of energyconsumption, the symbol H denotes that the advanced controlstrategies can achieve significant energy savings compared withtheclassicalcontrolsystems.Theenergysavingspercentagedepends on weather conditions, building characteristics and userpreferences.

IV. AGENT-BASEDINTELLIGENTCONTROLSYSTEMS

VariousresearchersdefineArtificialIntelligence(AI)indifferent ways. The differences in the definition of AI have twodimensions: One is human centrality and the other is rationality.The aspect that intelligence deals with rational actions is mostlyadopted. In this view, intelligence deals with the approach to theproblems through the laws of thinking; in other words, throughclearprocessesofreasoning(Aristotelianreasoning).Therationalapproachresultsinsystemsthatareacombinationofmathematicsandtechnology.Thus,AIinvolvessystemsthatoperaterationally.

IAQ control(CO2	Visual comfortcontrol (illumination)	Energyconsumption	Globalcontrolstrategies	Prioritytopassivetechniques	Userpreferences	Learning	Tuning: fuzzysystems orGAorneural adaptation	Temperature control	Adaptation	DCV ventilation control	Source ofreferen
–	–	–	–	–	–	–	–	H	–	–	[13]
–	–	H	–	–	–	–	–	H	–	H	[13]
H	H	H	H	H	–	–	–	–	–	H	[36,68]
H	H	H	H	H	–	–	–	–	–	H	[67]
H	H	H	H	H	–	–	–	–	H	H	[67,37]
H	H	H	H	–	H	–	–	–	–	–	[72]
H	H	H	H	H	–	–	H	–	–	H	[55]
H	H	H	H	–	–	–	H	–	–	H	[37,57]
–	–	H	–	–	–	H	–	–	–	H	[41,46,75,76]
H	H	H	H	H	H	H	H	–	H	H	[112,116,121, 123,117]
–	–	H		H		H		–	–	H	[27,82]
H	H	H	H	H	H		H	–	–	H	[10,11,44, 66,117]
H	H	–	H	H	H	H	–	–	–	H	[118,119]
H	H	H	H	–	H	H	–	–	–	H	[69,120,121]
H	H	H	H	H	H	–	H	–	–	H	[61–63]
–	–	H	–	H	–	–	–	H	H	H	[22]
H	–	H	–	–	H	–	–	–	–	H	[19]

Table 2
Comparisonofcontrolsystems.

Controlsystems	Thermalcomfort control (PMV)
ON/OFF	–
PID	–
Fuzzy PcontrolFuzz	I
yPIDcontrolAdaptiv	I
efuzzy PD Fuzzysyst	I
emsFuzzy PIcontrol	I
Adaptivefuzzy PI	I
Neuralnetworkcontrol	I
Agent-based	I
intelligentcontrol	I
Predictive	
controlSupervisoryc	I
ontrol	I
Reinforcementlea	I
rningcontrol	
Ambientintelligent	I
Self-adaptive	I
control	
systemOptimal	–
controlOptimala	–
nd	

IntheapproachofAIthroughthelawsofthinking,emphasisisgiven to the correct derivation of conclusions. Best results areachieved when rational action is applied and this can be done byusingrationalagents.Arationalagentactsinawaythatisoptimalinregardtoeithertheclarityorambiguityoftheinformationthatitaccepts.Consequently,theuseofrationalagentsisfundamentalinthe AI approach. A rational agent that realizes the best possibleactioninagivensituationisanintelligentagent.

In controls and robotics, intelligent agents are designed andimplemented. In automatic control, a controller has the char-acteristics of an intelligent agent. The properties of the environ-ment are very important and have significant implications on thedesignofcontrollersandrationalagents.Classicalautomaticcontrolsystemsdealwithenvironmentsthatarecausalandobservable. In stochastic and observable environments, optimalstochastic control is applied, and in environments that involveboth continuous and discrete time subsystems hybrid control isapplied.

AttheAIlabofMassachusettsInstituteofTechnology(MIT),Brooks and his group [106] work on an intelligent room projectthatfocusesmainlyontheuserandthefacilitiesofferedtohim/herintheroom.Forthis reason,cameras,microphones,etc.areinstalledinthebuildingtocontrolvoice,monitorfacesandgestures, etc. This is a new research direction in control systemsbuildings. In the various zones of the building, controllers areconsidered as distributed software agents [107]. Intelligence isdistributed to agents and evolves through the connections andinteractionsoftheagents.

4.1. Multi-agentcontrolsystems(MACS)

Manytimes,controlengineersfacecomplicatedcontrolproblems where they have to design and implement real timecontrol systems that use a group of controllers instead of a singleone.Inaddition,thehumanfactorisinvolvedinthecontrolsystem,eitherrewardingornotrewardingaspecificcontrolstrategy(reinforcement learning). These systems are called Human CentricSystems[108].Now,thecontrolengineerhasonemorejobtodo:that of breaking the problem into many simple sub-problems(structuring).Thedesignofthemulti-controllersystemisperformed and the system is implemented on a more generalframework, based on controllers–agents. For optimal operation,thecontrollers–agentsareguidedbyacoordinator–agent[109].

Aswestatedinthepreviousparagraphs,inordertocontroltheusers’environment,researchershavefollowedvariousapproaches;e.g.neuralnetworksbasedontheconventionaltheory of mechanical learning. However, these approaches useobjectivefunctionsthataimeitheratderivingaminimizedcontrolfunction that satisfies the users' needs on an average level, or atoptimization between a numbers of conflicting needs (e.g. energyefficiency and users' comfort). In both cases, users have limitedparticipation in the operation of the system and for this reason;theymusttoleratesomedegreeofdiscomfort.

One solution to this problem is offered by combining systemsbased on behavior (behavior-based systems) with systems basedon Computational Intelligence [106,110,111]. The main advantageof the and ''nomos'' (rule or law). A system is autonomous when itsbehavior changes following a fundamental law. For example,biological systems are autonomous because they operate withmechanismslikeself-organization,evolution,adaptationandlearning. Methodologies and techniques developed for intelligentautonomoussystems,likemobilerobots,havebeentransferredtoand applied to buildings in order to equip them with intelligence[106,112]. In [112] the authors have developed a multi-agentsystem based on fuzzy logic and genetic algorithms. The systemconsists of three constant behaviors: (a) security, (b) danger andeconomy, and (c) a comfort behavior adapted to the action andbehaviorofthehabitants.

4.2. Architectureofamulti-agentcontrolsysteminbuildings

Techniques that divide a problem into smaller sub-problems,which are consequently solved, are called divide-and-conquertechniques [113]. They also constitute a top-down process. Ingeneral, there are no standard or classical methods to optimallydivideaprobleminsmallersub-problems.Eachcomplexproblemhasitsownpeculiaritiesanditsanalysismayrevealtheappropriate ways to perform the task. Therefore, people try toinventheuristictechniquestodothejob. Inthiscase,wesolvethesub-problemsbydesigningcontrollers–agentsthatarebasedonfuzzylogicandcanbeoptimizedbyusinggeneticalgorithms.Anintelligentsupervisor [54]coordinatestheoperationofthecontrollers–agents.Itisanimportantprocedurebecauseitleadstothenormaloperationoftheentiresystem.Inotherwords,itsolvestheoriginalproblem.TheconceptofanIntelligentAgent(IA)has systems that are based on behavior is that they reject atheoretical model and replace it by the real one. The behavioralsystem is a fuzzy controller where a genetic algorithm regulatesthe knowledge basis and the membership functions. The fuzzycontroller's outputs are weighted by the coordinator and thenforwardedtotheactuators.

Thecontrolsystemsthathavebeendeveloped byusingclassicaltechniquesofAIareautomatedbutnotautonomous.Thewordautonomous comesfromtheGreekwords''auto''(self) beenintroducedrecentlyintheareaofcomputerscience[114].Ithasbeenusedextensivelyin thefieldofArtificialIntelligenceandisclosely relatedtothesubjectofdistributedproblemsolving[113,115].

An IA consists of a virtual entity (software) that mainly has thefollowingproperties:

(a) Ithastheabilitytocommunicateandinteractwithitsenvironment.
(b) Itisabletoperceivethelocalenvironment.
(c) Itisguidedbybasic''objectives''.
(d) Ithasfeedbackbehaviors.

Thedesignofamulti-agentcontrolsystemconsistsroughlyofthreesteps[115]:

1. Structuring:Decomposethewholeproblemintoasetofindependentpartialproblems.
2. Solvingindividualsub-problems:Solvethepartialproblemsbydesigningcontrollers–agentsthatknowhowtosolvethepartialproblems.
3. Combining individual solutions: Combine the set of implementedagents into a coherent whole by properly coordinating theiractivities.

4.2.1. Decompositionoftheproblemofenergyefficiencyandcomfortinbuildings

The goal of obtaining comfort conditions and simultaneouslyenergyconservationinabuildingissolvedbythedevelopmentofintelligent systems. Mo and Mahdani[116] developed an agent-based framework for building operators and individual occupantsto negotiate their control activities. Dounis and Caraiscos[54]proposed the use of an intelligent supervisor that coordinates theoptimal cooperation of the local controllers–agents. The result isthattotalcontrolisachieved,occupants'preferencesaresatisfied,conflictsareavoidedand energyconsumptionisconditionally minimized. In a building, the controlled variables are the PredictiveMeanVote(PMV)index,theIlluminationlevel(lux),andtheCO$_2$concentration (ppm). The actuators that are being used are theauxiliary heating/cooling system, the mechanical ventilation, theshading,andtheelectriclighting.

In order to control the entire operation of the building, five localintelligent field controllers are developed and optimized off-line byusing Genetic Algorithms. These five lower level controllers areguidedbyahigherlevelIntelligentCoordinator.TheideaispresentedinFig.3.
Inputsandoutputsofthelocalcontrollersare

ControllersFCA$_1$andFCA$_2$—Inputs:illuminationerroranditsrate of change; Outputs: control signals to the shadowing andelectriclighting.
Controllers FCA$_3$ and FCA$_4$—Inputs: PMV error and its rate ofchange;Outputs:controlsignalstotheheating/coolingsystem.Controller FCA$_5$—Inputs: CO$_2$ concentration and its rate ofchange;Outputs:controlsignaltothemechanicalventilation.

Thecommunicationoperationofacontroller–agentwithitsenvironmentissketchedinFig.3.ForeachcontrollerlagentFCA$_i$,i=1–5 thereis the activation signal w_i¼fðinputs$_i$;q$_i$Þ, where variable $q_i$denotes the state of the controller–agent, and the acknowledge signala$_i$ that makes the controller–agent active(q_i=1)orinactive(q_i=0).
Ineachsamplingperiod(timestep),thecontroller–agentperforms a set of communication tasks. First, it receives a sample ofmeasurements and uses it to calculate the activation signal $w_i$andsend it to the coordinator/supervisor. This signal denotes that thecontrollerwantstobecomeactiveorinactive.Whenthecoordinator receives activation signals from all the controllers–agents, it makes its decision and sends acknowledge signals back tothem.Ifacontroller–agentreceivesapositiveacknowledgesignal,itbecomesorstaysactive;otherwiseitbecomesorstaysinactive.Also,ifacontroller–agentisactive,itcalculatesthecontrolactionandsendsittotheactuators.

4.2.2. Structureoftheintelligentcoordinator

The proposed intelligent coordinator is shown in Fig. 4. Itreceives as inputs PMV, IAQ, illumination level, energy consump-tion,occupants'preferences,andactivationsignalsfromthecontrollers–agents. It then performs two specific tasks using amaster-slavecoordinationmechanism.Eachtaskrequiresaseparate intelligent agent. The dependency between the two tasksisthatthelowerlevelagent(slave)operatesonlywhenitreceives an activationsignal rfromthe upper levelagent (master) [109,115].Inputs_1:Predictedenergyconsumption,andtotalcomfort[55].Inputs_2:E_{PMV}, DT_{out},E_{Iin},E_{Iout},DE_{out}whereE_{Iin}istheindoorilluminancedesiredminustotalindoorilluminance,E_{Iout}isthe illuminance desired minus outdoor illuminance, DE_{out} is thechangeofoutdoorilluminance(k)–outdoorilluminance(k—1),

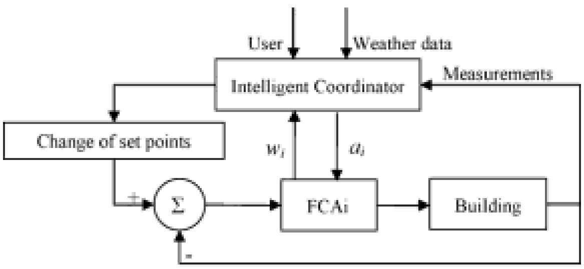

Fig. 3. Block diagram of the controlled system, the controllers–agents, and theintelligentcoordinator.

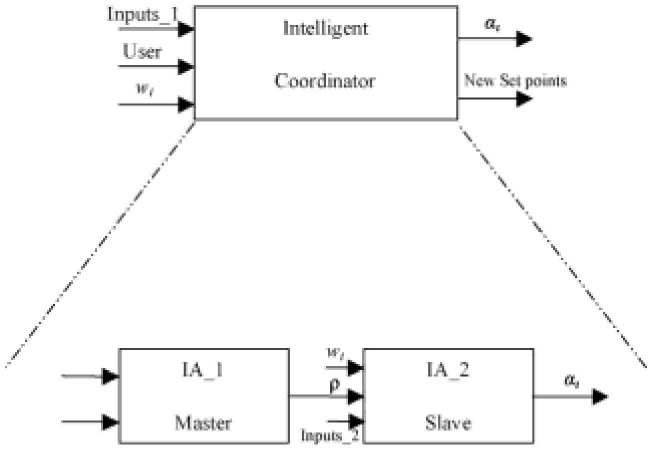

Fig.4.Structureoftheintelligentcoordinator.

E_{PMV}istheerrorofPMVand$DT_{out}=23^0$—T_{out},andT_{out}istheoutdoorambienttemperatur e.

- ThefirstIA(IA_1),calledmasteragent, evaluatestheenergyefficiencyandcomfortofth ebuildingandmonitorsthe occupants' preferences. By equipping the master agent withqualitative fuzzy rules, the inference engine machine producesnew set points. Activation signal r makes active or inactive IA_2.TherulesthatareusedhavetheformIF–THEN,forexample, IF Predicted Energy is small AND Comfort is low THEN Changeof set points. More details can be found in the paper Dounis–Caraiscos[55].
- The second IA (IA_2), called slave agent, compensates the interaction of the controlled sub-systems and manages to avoidconflictsbetweenthem;asforexample, betweennaturalventilationandmechanicalc ooling,naturalventilationandheating, shadowing and heating or cooling, decrease of directsolarradiationandvisualcomfort,etc.V eryoften,evaluationofthe control strategy is based on subjective criteria. Therefore, IA-2useslinguisticrulesthatstemfromphysicalla ws[48,53] and

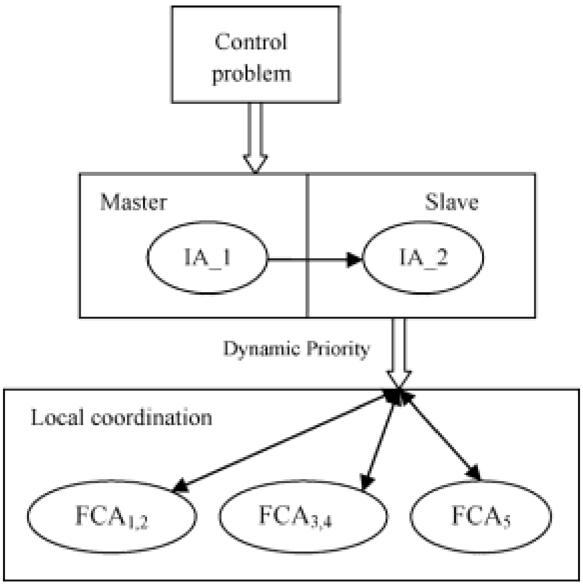

Fig.5.Organizationdiagramoftheproposedcontrolalgorithm.

forthecontrolprobleminabuildingenvironment,whereamaster–slavecoordinationmechanismisadopted.Intelligentagent IA_1 is the master agent and intelligent agent IA_2 is theslave. The organization diagram exposes the interaction betweensub-problems, which is confronted by the coordination mechan-ism. In the lower level, coordination is local with dynamic priority.Thepriorityofeachfieldcontrollerisdecidedby IA_2.

4.2.4. Uncertaintyinuser'spreferencesusinga-levelset

The desired value or set point is chosen as a trapezoidal fuzzyinterval whose membership function is illustrated in $_i$ Fig. 6. Thetrapezoidaltype-1fuzzysetequippedbyana-cutlevelcaneffectivelymodeltheuncertainty ofcomfort[117]. Thecoreiscomposedofthemostacceptableuser'spreferencesandthefuzzyintervalisdefinedas

aninferenceenginethatgeneratesacompensationpolicy.Thispolicyisdecisiveastotheincreaseofthesystem'sperformance.

½xd—;xdþ] ¼½xd—

þaðx

d—xd—Þ;xdþ

—aðx

dþ—xdþÞ]

SlaveagentIA_2consistsoftwoFuzzyNegotiationMachines(FNMs)[55].Anexampleofarule usedbyFNMsfollows:

If$E_{Iin}$is(NEorPO)and$E_{Iout}$is(NEorZE)andDE_{out}isZEthen

Thedesirevaluesbelongtointerval½x_d—d^a;x_dþd^a],x= {PMV, CO_2,ILL},where$x_d$isthesetpoint,x_d— and$x_d$þdenotetheupperand lowerboundsofx,respectively,andd^a¼x —aðx—x Þisthe

x_d x_d 0 0 1

NP NP

x_d dþ

dþ dþ

$a_1$isOFFand$a_2$isON.

bandaroundthedesiredvalue.Thea-cutoffuzzydesiredvaluesis

IfE_{PMV}isNEandDT_{out}isNEthena^{NP}isOFFanda^{NP} isONand

3 4

a^{NP}isON.

wherea^{NP}ðkÞaretheoutputfromFNM1andFNM2,anda_i(k)isthe acknowledgement signal. For more see Ref. [117]. The two IAscanbeviewedaspartsofanintegratedrealtimedecisionsupport systemthatderivescompensationactionsinordertoincreaseenergyefficiencyofthebuilding,minimizetheconflictsthatarisefrom the simultaneous operation of the controllers and satisfy theoccupants'preferencesbyobtainingthermalandvisualcomfort.

Theaboveanalysisshowsthatintelligenceoftheentiresystemis embedded not only in the controllers–agents but also mainly inthestructureoftheircommunication.

4.2.3.Organizationdiagram

The result of the design of a multi-agent control system is ahierarchicalorganizationofintelligentagents,calledtheorganiza-tiondiagram.Inessence,theorganizationdiagramisamodelthatrepresents the operation of a multi-agent control system. Fig. 5showstheorganizationdiagramoftheoveralllcontrolalgorithm

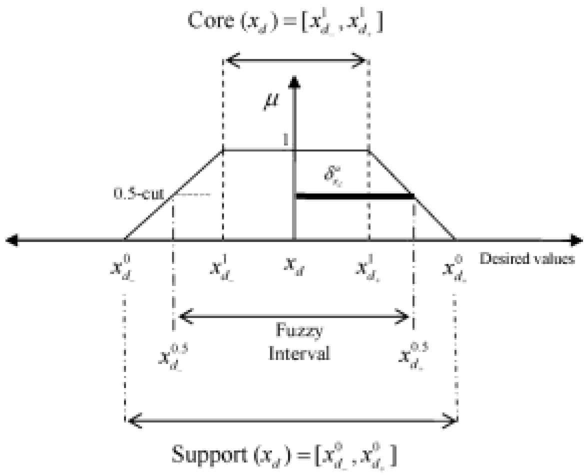

Fig.6.Trapezoidalfuzzyintervaldesiredvalues.

thesetofallvaluesof$x_d$satisfyingtheuser'spreferencesatleastwithadegreeofpreferenceoracceptancea=0.5.Wehavechosen ¼75ix;d 0:5 2

d 0:5
PMVd
¼0:4,dILLd
0:5
CO
d

4.2.5. Computingthemembershipgradeofmeasurements PMV,ILL,andCO_2usinga-levelfuzzyset

Thefuzzy a-cutor a-levelfuzzy setofA characterizedby
Ã¼AðxÞifAðxÞ≥a or
a 0 otherwise
ÃΞfðx;mðxÞÞjx2Ag a A a

Basedontheabovedefinition,wecanconcludethata-levelfuzzy set is obtained by reducing part of the fuzziness in the originalfuzzyset[117].

In each iteration, the membership grades of the measurementsPMV,ILL,andCO_2arecomputedbythea-levelfuzzyset(Fig.7).Thesegradesdetermineapointinafuzzycube.

4.2.6.A3Dfuzzymodelforglobalcomfort

Theunitcubegeometryofdiscretefuzzysetsassistsuswhenwedefinefuzzyconcepts.Thecomfortisrepresentedasaninformation granule; the size of granules is problem-oriented anduser-dependent.Inparticular, the size of information granule ofthe comfort consists of three parts (PMV, ILL, CO_2), and the formalrepresentation of this information granule is a fuzzy set in a fuzzycube [55]. Therefore, a 3D discrete fuzzy set models higher leveluncertainty than does a Type-1 FS. This technique opens up anapproachablewayformodelinghumandecision-making.

Let V be a set of three elements V ¼ fPMV$_d$; CO_{2d} ;ILL$_d$g. Thenonfuzzypowerset2Vcontainseightsets.Thesesetscorrespond respectively to the eight bit vectors (0,0, 0), …, (1, 1,1).Empty set **1** lies at the origin (0, 0, 0) of the cube, and space V lies at vertex(1,1,1). The 1 and 0 s indicate the presence or absence of the ithelement in the

IfcandVarenonemptythenE(c,V)=E(V,c)2[0, 1],E(c,c)=1andE(c,1)=0.Thefuzzyequalitymeasuregivesavaluenear1if

¼50ppmv.

the two fuzzy sets equal well. It gives a value near 0 if they equalpoorly.The3Dfuzzycomfortsetisanewrepresentationfor

the word ''comfort'' [117]. This methodology of approximationrepresentationofthecomfortisverysignificantbecauseitisusedintheprocedureofdecision-makingforthemasteragent.

4.2.7.Simulationresults

AtrapezoidalMFisdefinedasaquadruplex{*a*,*b*,*c*,*d*}where

subset. A fuzzy subset c ⊂ V defines the fuzzy unit(fit)orfitvector:
c¼ðmPMVa;mCOa;mILLaÞ 2I¼½0;1]
d 2d d
pointin fuzzy cube

– mc¼½c;c̄] ⊆½0;1]
c and c¯ denote lower and upper bounds, and
– mC denotes an intervalset,thatis,thesetoftherealnumbersfromc¼atoc¯¼1.
Thefuzzya-cutsetofmeasurementvariablesPMV(k),ILL(k),
CO_2(k) defines a 3D fuzzy comfort set c with membership functionmC. If a = 0.5 then the 3-D fuzzy set is a cube with origin (0.5, 0.5,0.5)andtheoptimalcomfortvaluecorrespondstothevertex(1,1, 1).Usingthesymmetricfuzzyequalitymeasure[117]wemeasures the degree to which fuzzy set c matches fuzzy set V,thatis,themembershipgradeof3Dfuzzycomfortset:
these parameters (with a <b ≤ c <d) determine the coordinates ofthe four corners of the trapezoidal MF. In particular, the users'preferencesforcomfortconditionsarespecifiedviatrapezoidal fuzzysetswiththemembershipfunctionsoftheform:
T_1(PMV;PMV_d—0.5,PMV_d—0.3,PMV_d+0.3,PMV_d+0.5).
T_2(ILL;ILL_d—100,ILL_d—50,ILL_d,ILL_d+50,ILL_d+100).
T_3(CO_2;CO_{2d}—75,CO_{2d}—25,CO_{2d},CO_{2d}+25,CO_{2d}+75).
where, as usual, the parameters denote the characteristic points ofthe piecewise membership functions of the fuzzy sets (see Fig. 6).The first, one trapezoidal form T_1, Eðc;VÞ¼m
¼Degreeðc¼V

cardinalityðc\VÞ

can be regarded as a descriptor ofuser's preference regarding the PMV, where PMV_d= 0. The secondform,T_2,characterizestheuser'spreferenceregardingtheilluminance,whereILL_d= {800–600–500–800} lx.The last one,T_3, describes theuser's preference of CO_2concentration,where CO_{2d}=1000ppmv.Inthesimulationexamplethea-cutoffuzzy
desired values is a = 0.5. The simulations concerned a passive solarbuildingcharacterizedbyanimportantsouth-facingwindow,glazedarea(3m^2),area45m^2,volume135m^{3}andbyahigh
thermal inertia, light transmittance of the window glazing mean(t = 0.817), reflectance of all indoor surfaces (r = 0.4) [117]. In theTRNSYSthereisanelectriclighting(10lamps),ashadingdevice (curtain)andheating/coolingactuator.Simulationtimestepis6min.
The performance of the agent-based intelligent control systemapplied in a single zone building is evaluated. Some significantresults (16 July) are shown in Figs. 8–13. Figs. 8–10 present timehistories for of the PMV index, illuminance and CO_2. These figuresillustrate that the comfort conditions are maintained within theacceptablelimitsoftheusers'preferences.
Fig.11showsthetimeevolutionofmembershipgradeofnewfuzzycomfortvariable withinthe3Dfuzzycomfortsetwithdegreeofacceptance>0.65.
Fig.12givesthecurvesofthedailyandpredictedenergyconsumption.Energyconsumptionandcomfortusuallyaffect

cðkÞ
P
¼P 1
3
i¼1

minðci;ViÞ
maxðci;ViÞ

Þ ¼cardinalityðc[VÞ

wherekisthediscretetimestep.ThefuzzyequalitymeasureE(c, V)measuresthedegreetowhichfuzzysetcequalsfuzzysetV.

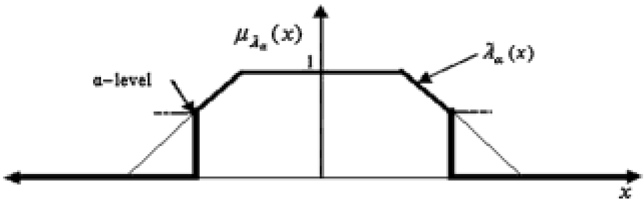

Fig.7.Thea-levelfuzzysetoffuzzysetA.

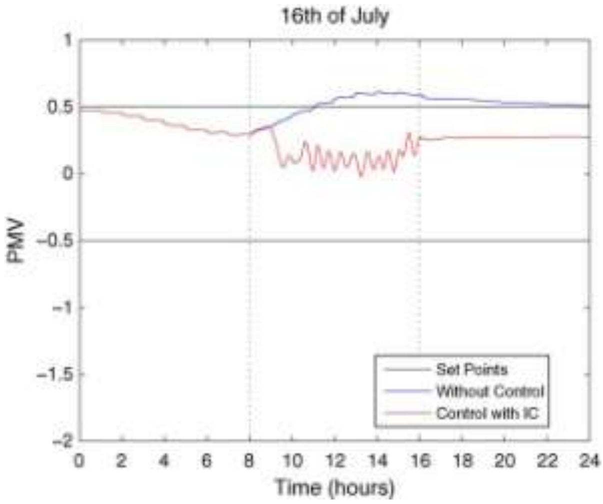

Fig.8.TimehistoryofPMV.

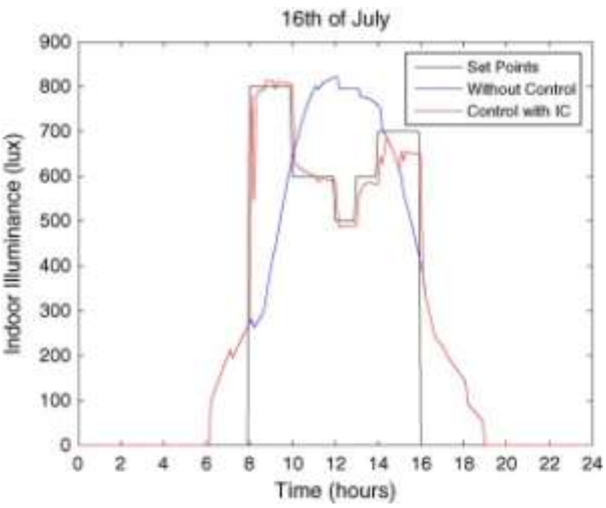

Fig.9.Timehistoryofindoorilluminance.

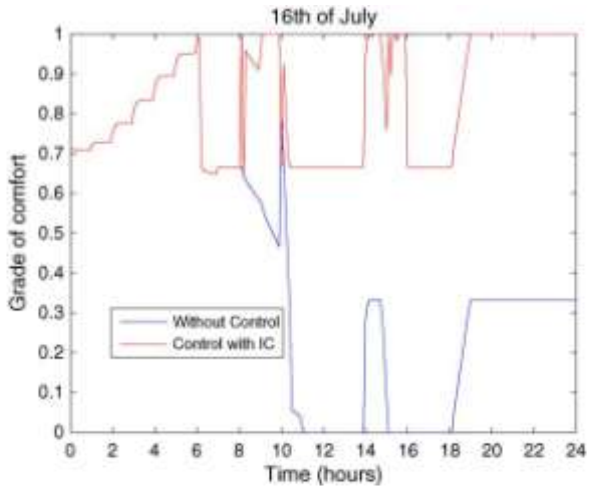

Fig.11.Timeevolutionofcomfort.

eachotherinoppositeways.Theoptimizedagent-basedintelligentcontrol system improves occupant's comfort while the energysavings is significant. Fig. 13 presents time history of the PPD.These simulation results indicate that the Percentage of PeopleDissatisfied (PPD) index [4] is less than 6% and therefore it ismaintainedwithintheacceptablelimits(below10%).

4.3. Reinforcementlearningagent

Dalamagkidis et al. [118] have developed a reinforcement-learning controller that takes into account user preferences inorder to achieve energy savings, high comfort and indoor airquality. The advantage of this approach is that the reinforcement-learningagentcontinuouslylearnsfromdifferentcharacteristicsofthebuildingsandimprovesitspolicy.However,thisreinforcementcontroller temporarily increases users' dissatisfaction and totalenergyconsumption.

Anderson et al. [119] used a reinforcement-learning agent inparallel with an existing feedback PI controller. This combination isdesigned within a robust control framework. Its main goal is toimprove the control of a non-linear model of a heating coil. Theresults show that the reinforcement learning agent learns how tomodify the PI controllers' output only when the PI controller in notadequatetosatisfythecontrolobjectives.

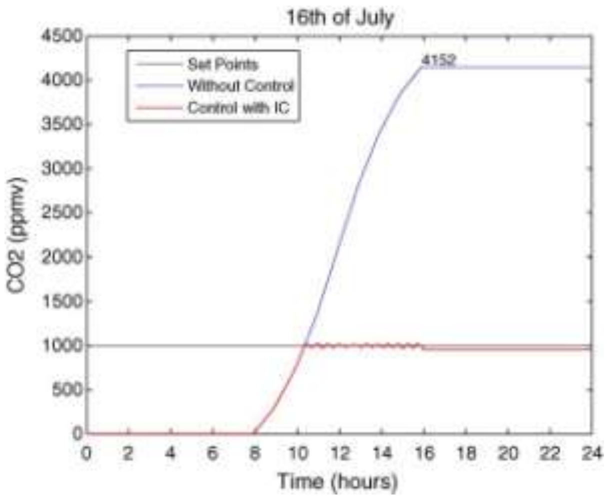

Fig.10.TimehistoryofCO$_2$.

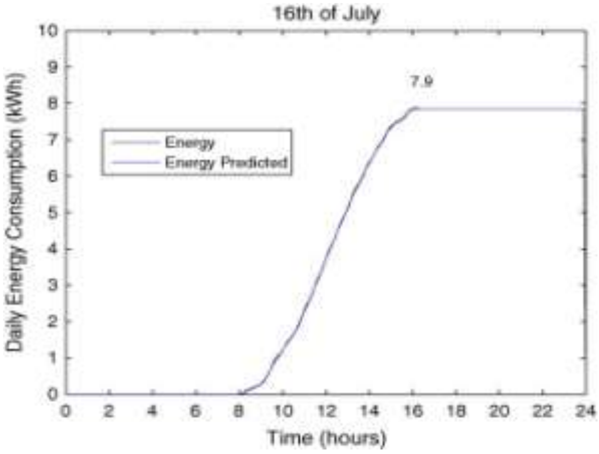

Fig.12.Timehistoryofthedailyrealandpredictedenergyconsumption.

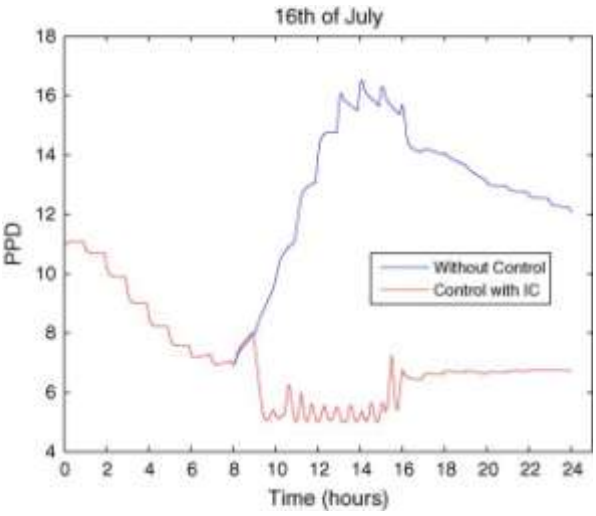

Fig.13.TimehistoryofPPD.

4.4. Ambientintelligence—AMI

In[106,107,120,121,69,122,123],theauthorsdealwiththescenario of ''Ambient Intelligence—AmI''. AmI is a new paradigm ininformation technology that ''triggers'' imagination. It is a digitalenvironmentthatperceivesthepresence ofusers and adapts totheir needs, depending on their behavior. In such environments,interconnectedintelligentfuzzy agentsareused.Theseagentssupporttheusers'actionsandtheeffectorsofthebuilding.Experiments performed at Essex intelligent dormitory showed thatthissystemcouldapproachtheideaofanIntelligentEnvironment.

V. CONCLUSIONS

5.1. Thesurvey

Inthisarticle,wepresentedareviewof controlsystemsforenergymanagementandcomfortinbuildings.Atthebeginningofthispaper,wedefinedtheproblemasawhole,whereeenergy,comfortandcontrolareinvolved.Next, wepresentedconventionalcontrolsystemsforbuildingsandtheirdisadvantages.Thedevelopmentofintelligentcontrolsystemsintheframeworkofcomputationalintelligencehassetthebasisforimprovingtheefficiencyofcontrol systemsinbuildings.Newwaysofdesigninghuman-centricsystemsarosefromthedevelopmentof thescientificfieldofcomputationalintelligence.Applicationofsuchsystems to buildings results in the so-called ''intelligent buildings''.Thearchitectureofamulti-agentcontrolsystemforenergyefficiencyand comfortinabuildingenvironmentwasthenpresented.Infinishing,wereferredtoanewparadigmininformationtechnology,AmbientIntelligent,whichisanewapproachtowardsthecreationofanintelligentbuildingenviron-

ment.Implementationmethodsformulti-agentcontrolsystemsareFuzzyLogic,Neural Networks,Neuro-FuzzySystems,MarkovChainModels,FiniteStateAutomata,LearningAutomata,Depen-denciesOrganization,etc.
Acomparisonhasbeenmadebetweendifferentadvancedcontroltechniques.Themaincomparativeresultsare:

- The fuzzy PI (or fuzzy P) control algorithm is adequate for thelocalcontrollers.
- The tuning of the fuzzy PI controller could be achieved on-linewith fuzzy system [50] and off-line with genetic algorithms[100].
- Inintelligentcoordinatorlevelcouldbeusedpredictivecontrol givingprioritytopassivetechniquestoachievecomfort.
- Basedonusers'preferences,theoptimumtuningofset-pointsofthecontrollersisachievedbysupervisorycontroltechnique.
- The on-line learning of the control system with reinforcementlearningmethod.
- Allmentionedadvancedcontrolsystemssatisfytheindoorrequirementswithinacceptablelimitsandsimultaneouslyachieveaconsiderablereductioninenergyconsumption.
- By using these advanced control systems, high comfort levels andenergysavingscanbeobtained.Itshouldalsobementioned, however,thattherearesomelimitationsinpractice.Forexample, theuser'sactivitylevelandthermalresistanceofclothing,involvedinthePMVequation,cannotbemeasuredbysensors. The cost reduction of the PMV sensor would have a greatpotentialfortheHVACapplication[46].
- Advancedcontrolsystems aredefined asintelligentcontrol systems, and include two levels. The first level is a low-levelfeedbackcontrolofindoorconditionsforeachbuilding'szone.Thesecondlevelisahigh-levelsupervision(intelligentcoordinator)andplanning.Thishigh-levelmanagementprovidesoptimal operation strategies for energy conservation and environmentalcomfort.Therefore,anadvancedcontrolsystemrepresentsabasicstructural unit in an integrated indoor environment and energymanagementsystem.

5.2. Futureperspectives
Futuretrendsandopenquestionsthataremoregeneralaregivenhere.

1. EnergyIssues,OtherFactors(Weather,BuildingDesign,Occupancy, etc.), Thermal comfort issues, Passive Solutions(Architectural and Structural Design), Naturally Ventilated andMixedModeBuildings.
2. Hierarchical and supervisory control structure using autono-mousagents—'divideandconquer'approach.
3. Balancebetweenthermalcomfortandenergyusage.
4. Hybridcontroltheorythatcanbeusedtodesignasupervisorycontroller. The task of a supervisory controller involves theoptimalcontrol-basedsetpointpolicygeneration.
5. Agent–controller methodology from artificial intelligence canbe used for coordinated task achievement. Learning paradigmsforagents:
   - learningfeedforwardrandomneuralnetwork[124];
   - random neuralnetworkswithreinforcementlearning[124];
   - adaptivestochasticfinite-statemachines[125].
6. AmbientIntelligenceSystems.
7. Open-LoopCoordinatorofLocalControllers.
8. Closed-LoopReal-TimeOn-lineLearningAbility.
9. Type-2 fuzzy sets [126], order-2 fuzzy sets [55] or Routh setssupportingthedevelopmentofhigher, conceptuallycompositeconceptsforcomfort,userpreferences,andenergy.
10. Granular Computing (GrC) as a new paradigm of Computa-tional Intelligence in user-centric systems [108]. The collectionofcomplexinformationentities(thermalcomfort,visualcomfort and indoor quality) can be considered as an informa-tiongranule.
11. Thedecreasingcostofhardwareandimprovementsinsoftwarewillmakethewirelesssensor–actuatornetworksveryusefulinthecomfortcontrolofbuildings[127].

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