An Integrated Building Management Platform for Investment into Renewable Energy System and SRI Compliance

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Abstract: The goals of ecological transition in habitations require an increasing number of considerations to ensure that newly installed systems or building management solutions are economically advantageous and effective in terms of energy savings and production. The increasing variety and supply of renewable energy systems, and the increasing demand for them require tools that meet the needs of building stakeholders (e.g., building owners and facility managers) to ease the transition as well as provide consistent metrics to measure the validity and integrated simulation to facilitate investment decisions and track ecological transition progress over time. This paper introduces a comprehensive toolset with multiple features, including the simulation and management of Renewable Energy Systems (RES), the Building Management System (BMS) integration, and the calculation and simulation of the Smart Readiness Indicator (SRI). This toolset collectively assesses the readiness of a building toward an ecological transition. Specifically, the system includes: (1) an Advanced SRI Calculation Engine, which implements both simplified (Method A) and detailed (Method B) SRI calculations for various European regions providing precise evaluations of smart building capabilities across domains such as heating, cooling, ventilation, lighting, and energy monitoring; (2) a continuous tracking of building's smart readiness evolution enabled by seamless BMS Integration that allows real-time monitoring of building systems and allows a continuous tracking of a building's smart readiness evolution; and finally (3) an Optimized Investment Advisor which offers tailored recommendations for investments in smart building upgrades, renewable energy installations, and energy storage systems, employing advanced optimization algorithms to ensure cost-effectiveness and energy efficiency. Developed as part of the INSPIRE, an experiment under the SUSTAIN EU project Open Call for smart building innovations, this toolset aims to enhance decision-making processes, improve resource allocation, and foster a holistic approach to achieve smart, sustainable, and energy-efficient buildings.

1 INTRODUCTION

The INSPIRE (INteroperable open and modular energy management System with integrated Performance Improvement and optimization SRI calculation and support for energy and REnewable investments) endeavors to establish a modular, interoperable energy management system that incorporates an advanced Smart Readiness Indicator (SRI) calculator and supports investments in renewable energy sources. This initiative is focused on enabling building users to achieve independence from fossil fuels by using the SRI (*SRI Implementation Tools*, s.d.) to assess and enhance

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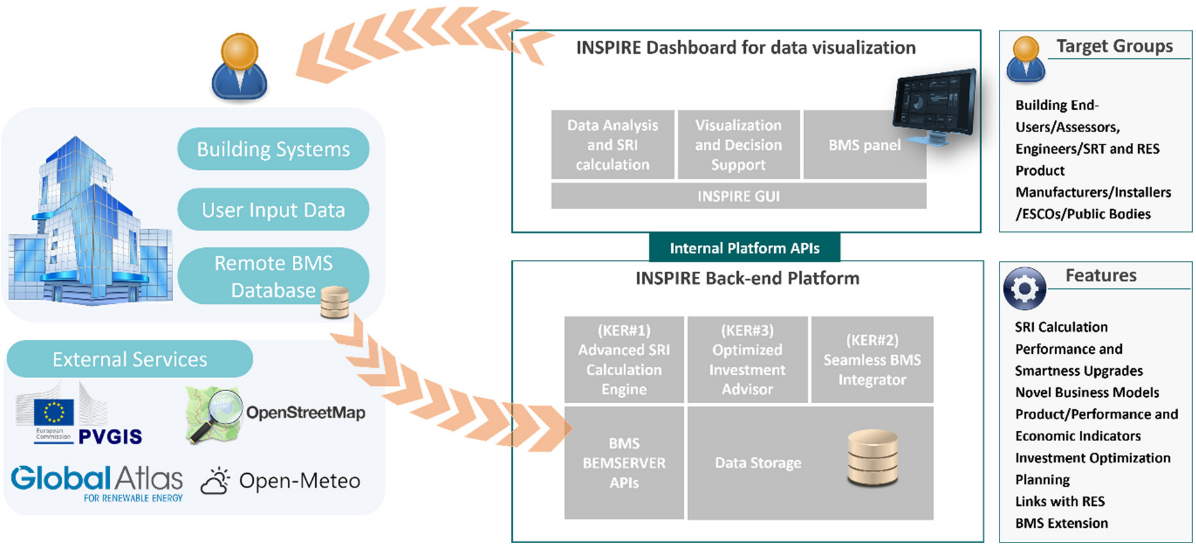


Figure 1: Conceptual architecture of the INSPIRE platform.

building capabilities, thereby facilitating investments in renewable energy systems (RES) and smart technologies integrated with advanced IT systems. The system comprises three primary software components. The first, an Advanced SRI Calculation Engine, offers a user-friendly platform for deep evaluation of a building's readiness for smart technologies. The second component, the Seamless BMS Integrator, leverages the BEMServer open-source solution to enable real-time insights and operational optimization, representing a significant advancement from static to dynamic SRI assessments through responsive building management. Lastly, the Optimized Investment Advisor component evaluates installations of RES (Verda et al., 2022) and smart devices to develop balanced investment plans that emphasize energy efficiency and reduce environmental impact. Collectively, these components illustrate the INSPIRE integrated approach to promoting sustainable and intelligent building environments.

2 LITERATURE REVIEW

The development of tools to assess a building's readiness for ecological transition aligns with the European Smart Readiness Indicator (SRI) framework, which emphasizes energy efficiency, smart technology integration, and user-centric adaptability. Several recent studies have highlighted the strengths and limitations of the SRI methodology across diverse contexts. For instance, (Apostolopoulos et al., 2022) explored retrofitting scenarios to enhance smart readiness in various building typologies, demonstrating cost-effective pathways to improve SRI scores but revealing inconsistencies in service applicability and subjective assessment criteria. Similarly, (Papadopoulos et al., 2024) proposed simplified financial indicators to bridge technical and economic considerations, promoting accessibility and adoption among diverse stakeholders. Comparative analyses, such as those by(Samaras et al., 2024), underscore the regional variations in SRI adoption readiness, highlighting gaps in policy frameworks and technological infrastructure across EU countries. These studies collectively underscore the need for a comprehensive, adaptable assessment toolkit that integrates SRI frameworks with real-time data, financial metrics, and multi-criteria decision-making models to ensure broader applicability and alignment with ecological goals. The tools presented in this paper contribute to this evolving landscape by offering enhanced methodologies and comparative insights, addressing previously noted limitations in SRI's adaptability and practical implementation.

3 SOFTWARE ARCHITECTURE

The Software Architecture is meticulously designed to consolidate various components to augment building intelligence, energy efficiency, and investment optimization through streamlined front-end and back-end interactions.

The architecture comprises a number of components, organised as follows:

Dashboard for Data Visualization: This dashboard employs HTML, CSS, and JavaScript to craft a user-friendly interface that supports data analysis, Smart Readiness Indicator (SRI) calculations, and visualizations. It incorporates tools such as OpenLayers for map integration, Ol-Geocoder for geocoding services, and DataTables for managing lists of buildings. The GUI enables building managers to effectively visualize data and interface with the Building Management System (BMS).

Back-end Platform: The back-end platform is engineered to facilitate critical functionalities including the Advanced SRI Calculation Engine, Optimized Investment Advisor, and Seamless BMS Integrator. This platform is integral in performing calculations that optimize investments and enhance building intelligence and energy production capacity. It integrates external data and utilizes APIs for real-time monitoring and data acquisition from IoT devices. The back-end supports the front-end dashboard through sophisticated data processing and decision-making tools, aimed at maximizing energy efficiency and optimizing smart building operations.

3.1 SRI Calculator

The Smart Readiness Indicator (SRI) is a European Commission initiative under the Energy Performance of Buildings Directive, designed to measure a building's capacity to utilize smart technologies that facilitate decarbonization and enhance living comfort and efficiency.

It evaluates a building's 'smartness' based on its ability to sense, interpret, communicate, and actively respond to the dynamics of technical systems, external environmental factors (including energy grids), and occupant needs.

The methodology for calculating the SRI is based on the multi-criteria assessment method defined in Commission Delegated Regulation (EU) 2020/21551 (*Delegated Regulation - 2020/2155 - EN - EUR-Lex*, s.d.) and provide two main Methods, the simplified one (Method A) which is based on a limited, simplified catalogue of 27 services and the Method B, based on lists full catalogue of 54 services.

The formula for calculating the SRI can generally be simplified as follows:

$$SRI = \frac{\sum_i W_{i,c} \cdot S_{i,c}}{\sum_i W_{i,c}} * 100 \qquad (1)$$

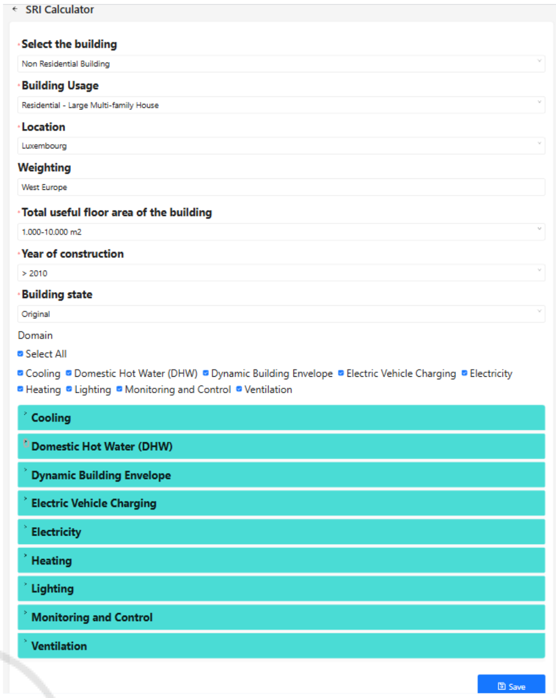


Figure 2: User-Friendly Data Input Interface for the SRI Calculator.

Where:

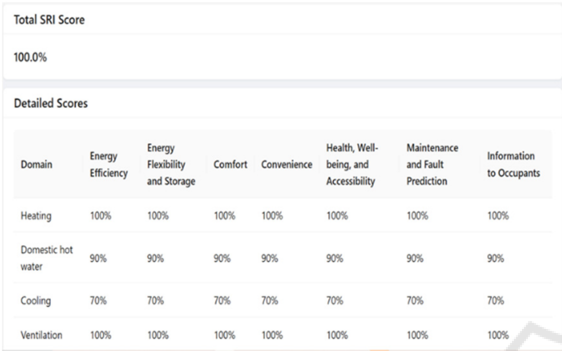
- $W_{i,c}$: Weight assigned to service i under the country-specific framework.
- $S_{i,c}$: Score of service i under the country-specific framework, which may include adjustments for local definitions or thresholds.
- $\sum_i W_{i,c}$: Total weight of all services after country-specific adjustments.
- The result is multiplied by 100 to express the SRI as a percentage.

This formula encapsulates the weighted average score of services adjusted for local conditions, expressed as a percentage.

A detailed SRI calculation tool using Method B has been implemented across all regions. The tool has developed and integrated essential components for calculating total SRI scores, impact scores, domain scores, detailed (partial) scores, and aggregated scores. All data are stored in a PostgreSQL database, managed through the Flask framework, with HTTP REST APIs enabling interactions with the Optimized Investment Advisor tool.

3.2 SRI Optimisation Component

The Optimized Investment Advisor tool delivers investment recommendations by leveraging SRI scores, budget limitations, and specific device catalogues relevant to Italy, the Netherlands, and Cyprus. It employs sophisticated optimization algorithms, such as the Knapsack Branch and Bound method (Bednarczuk et al., 2018), to propose optimal investment strategies that improve building intelligence. These recommendations are seamlessly integrated with the comprehensive SRI score obtained from the SRI Calculation Engine.


Total SRI Score

100.0%

Detailed Scores

Domain	Energy Efficiency	Energy Flexibility and Storage	Comfort	Convenience	Health, Well-being, and Accessibility	Maintenance and Fault Prediction	Information to Occupants
Heating	100%	100%	100%	100%	100%	100%	100%
Domestic hot water	90%	90%	90%	90%	90%	90%	90%
Cooling	70%	70%	70%	70%	70%	70%	70%
Ventilation	100%	100%	100%	100%	100%	100%	100%

Figure 3: User-Friendly Interface of SRI Calculator Results.

Below is a detailed description of the mathematical structure used for the calculations on the backend, which outlines how the optimization process is approached.

Objective:

Maximize the total "profit" (**Total SRI Score**):

$$\text{Maximize } \sum_{i=1}^{n} p_i x_i \tag{2}$$

Constraints:

The total "weight" (**cost**) of the selected items (**smart devices**) must not exceed the capacity (**Budget**):

$$\forall C \ \sum_{i=1}^{n} w_i x_i \leq W \tag{3}$$

Variables:

n: Number of items (smart devices).

w_i: Weight (cost) of item

p_i: Profit (total SRI score) of item

x_i: Binary decision variable indicating whether item i is selected (1) or not (0).

W: Maximum capacity (budget).

C: Cost type (Main Automation Cost, Installation Cost, Operational and Management Cost).

3.3 RES Optimiser

The RES optimizer provides the possibility to determine the best set of renewable energy systems, in order to maximise renewable energy production and incentivise self-consumption as well as production, in order to reduce reliance on the grid, given the market costs per kWh. The optimisation consists of minimising the LCOE using Constrained Integer Linear Programming techniques (Omu et al., 2013) as well as a Constrained Search Problems (Hannan et al., 2020), (Khan et al., 2020), (Yang et al., 2022). A number of devices are available as possible solutions for the energy optimiser, said options being photovoltaic panels, wind turbines, energy storage battery solutions, and micro co-generation plants to replace the older, less efficient boilers.

3.3.1 Building Selector

The building selector consists of providing an interface in order to find the building of interest on which to perform the analysis and optimisation of the potential Renewable Energy Systems to apply. The building selection then saves the building according to its coordinates, its local total irradiance value, and thus the potential performance with solar energy system, as well as the degree days in order to assess the potential heating energy required to activate the systems. Last but not least, the intuitive shape selection allows users to delineate the area of the building that will be used for their optimizations.

3.3.2 Optimization

The optimisation procedure allows users to select their preferred RES (Renewable energy systems) as well as provide further information about the building layout, about whether the building has a sloped or flat roof, the height of the available façade as well as roof availability percentage.

Next, there is the selection of potential RES to include in the optimisation. These are in turn divided into:

- **Photovoltaics (PVs):** based on the irradiance values obtained from PVgis (*PVGIS data sources & calculation methods*, s.d.) and considerations about PV panel degradation over ten years of use, reflecting the typical decline in energy production efficiency as PV panels age, the total power per PV is estimated and used to determine energy production
- **Vertical Axis Wind Turbines (VAWT):** the reason for VAWTs is their smaller form factor compared to the industrial case, allowing for decentralised wind energy production. Determining their energy is dependent on the maximisation of the energy produced by the rotor according to the Betz principle (van Kuik, 2007) and then the obtained energy production is used in the main optimisation function

- **Micro Combined Heat and Power (µCHP):** through the modelling of the internal building spaces, as well as the energy class in accordance to European and Italian standard as well as degree days estimation, it is possible to obtain a linear model of the shape factor and estimate the produced thermal energy and thus the recovered electrical energy of a µCHP within the optimisation
- **Energy Storage:** It is considered according to the type of profile the building is assigned to (office, apartment, warehouse) in order to determine the self-consumption and thus the sizing of the battery to maximise storage or minimise battery draw.

Finally, the system is optimised in accordance to the following objective function:

$$LCOE = \frac{\sum_{i \in S} C_i \cdot n_i}{\sum_{i \in S} G_i \cdot n_i} \tag{4}$$

Where:
C_i: cost per unit of the individual RES
G_i: revenue per unit fo the individual RES

LCOE standing for Levelized Cost of Energy. The feature of this function is being able to balance supply and demand of energy, to minimise costs and maximise self-consumption, thus reducing energy draw from the grid. Data about the building such as roof size, internal space, façade width and such determine spatial constraints and energy needs.

3.4 Building Management System Integration

In order to provide a complete solution, an existing building management has been incorporated through its core component and an API: Bemserver (Bourreau et al., 2019). BEMserver is an open source, AGPL-3.0 licensed, building management system with built in functionalities to manage buildings, districts, and apartments, as well as datetime data. This datetime data enables real-time insights and enhanced analysis, particularly in evaluating the impact of recommendations provided by tools such as acquisition campaigns. These campaigns are designed to monitor and assess the system's performance, allowing building managers to verify improvements in self-consumption or enhancements in the Smart Readiness Indicator (SRI) metric. This, in turn, boosts the building's interconnectivity and overall efficiency.

4 TESTS AND RESULTS

4.1 SRI Calculator Validation

The analysis in the table below showcases the assessment of differences between SRI scores derived from the EU Excel sheet for SRI calculation (SRI Package v4.5) and those calculated using the INSPIRE tool for buildings in Italy, across multiple levels of the different domains. Each domain's functionalities were tested independently to ensure accuracy, maintaining a 100% efficiency baseline for all her domains. The results for each level were then aggregated and averaged to determine the overall variance within the domain. This structured approach allows for a precise evaluation of the SRI tool's performance in comparison to the baseline data. The table also includes a breakdown of average percentage differences across various building domains, highlighting the minor discrepancies observed and providing a clear overview of the tool's consistency and reliability in SRI score calculations.

Table 1: Comparison of SRI Scores Across Europe: EU Excel for SRI calculation vs. INSPIRE Tool.

Average value of the Differences (In Percentage) for all the Regions					
Domains	West Europe	South Europe	North Europe	South East Europe	North East Europe
Heating	0.08%	0.02%	0.02%	0.03%	0.09%
Cooling	0.09%	0.03%	0.02%	0.11%	0.01%
Ventilation	0.02%	0.01%	0.05%	0.01%	0.01%
Domestic Hot Water	0.07%	0.06%	0.10%	0.03%	0.08%
Lighting	0.01%	00%	0.01%	0.0%	0.0%
Dynamic Building Envelope	0.0%	0.0%	0.01%	0.0%	0.0%
Electricity	0.08%	0.02%	0.04%	0.06%	0.10%
Electric Vehicle Charging	0.14%	0.14%	0.08%	0.14%	0.14%
Monitoring and control	0.06%	0.03%	0.06%	0.04%	0.01%

4.2 SRI Optimizer Validation

The SRI Optimizer has been tested and the tests implemented have confirmed that the knapsack algorithm provides accurate and optimal solutions for the given inputs, maximizing the Smart Readiness Indicator (SRI) scores within specified budget constraints, by correcting the minor issues in the functions of the optimizer and proving its effectiveness in decision support for smart device investments.

Table 2: Comparison of different tests implemented to validate the SRI Optimizer.

Country	Avg. Invest. costs	Avg. Initial SRI	Avg. Final SRI	Avg. Final investment	% SRI error
IT	5000	20	23	4988,1	0,15
		50	55	4993,16	0,06
	10000	20	26	9971,65	0,79
		50	59	9911,57	1,59
	50000	20	57	48432,3	5,72
		50	98	49086,7	2,17
	100000	20	100	92240,6	15,52
		50	100	99378,5	6,21
NL	5000	20	23	4991,69	0,21
		50	55	4976,42	0,12
	10000	20	28	9956,66	7,19
		50	59	9955,73	3,22
	50000	20	47	49454,87	14,45
		50	100	48756,88	24,86
	100000	20	100	94501,81	21,99
		50	100	98651,08	26,98
CY	5000	20	24	4986,55	0,25
		50	54	4999,33	0,01
	10000	20	27	9975,58	0,89
		50	58	9968,23	0,50
	50000	20	59	49578,4	10,14
		50	83	49708,34	4,81
	100000	20	100	99847,47	12,20
		50	100	97842,96	5,39

To facilitate enhanced Smart Readiness Indicator (SRI) scores and elevate the building's smart capabilities, users are prompted to select their country of interest currently available options include Italy, the Netherlands, and Cyprus. Additionally, users must specify their preferred cost type, choosing from Main Automation Cost, Installation Cost, or Operational Management Cost, along with their budget constraints. Utilizing the Knapsack Branch and Bound algorithm, coupled with a comprehensive device catalogue, the system strategically optimizes SRI scores by minimizing costs within the defined budgetary limits. The optimization outcomes are presented in terms of total equipment purchase cost and optimized SRI scores, accompanied by recommended investments. This allows users to meticulously review and consider suggestions for further enhancements, thereby fostering informed decision-making to improve the building's smartness effectively.

The Table 2 presents the results of tests conducted for Italy (IT), the Netherlands (NL), and Cyprus (CY) to evaluate the performance of the SRI optimizer across different investment sizes (€5,000, €10,000, €50,000, and €100,000) and initial SRI values (20 and 50). For each scenario, the average final SRI and average final investment calculated by the optimizer are reported, alongside the percentage error in SRI compared to the traditional calculation method using the EC spreadsheet. The data show that the SRI error generally increases with larger investments and higher SRI targets, with significant discrepancies observed particularly in the Netherlands at higher investment levels. This highlights the varying accuracy of the optimizer across different contexts and its performance relative to established methods.

4.3 RES Optimiser Validation

The RES Optimiser has been validated in accordance to a test set consisting of a variety of conditions in terms of location within Italy, as the Degree Day data was the most available, as well as provide diverse conditions in terms of climate due to the length of the country.

Outside of that, a number of conditions have been tested, namely:

Table 3: Input variables.

Parameter Name	Value set	
Building profile	Medium size apartment	
	Medium office	
	Warehouse	
Interior space	220 m^2	
	440 m^2	
	1760 m^2	
Energy consumption per square meter	80 €/m^2	
	120 €/m^2	
	160 €/m^2	
Energy classes	D	
	G	
BIPV Installation	Not expected	
	Installed on roof	
	Installed on wall	
μCHP	Not expected	
	Expected	
Location (latitude, longitude)	40.74805	17.38009
	41.87028	13.12521
	45.58191	12.76365
	40.304750	18.222830

As a result, the following algorithms were compared:

- COBYLA: gradient free optimization algorithm (Powell, 1994)
- SLSQP: Sequential Least Squares Quadratic programming (Joshy & Hwang, 2024)
- SHGO: simplicial homology global optimization(Endres et al., 2018)
- CP-SAT: Constraint satisfiability programming(*Python Reference*, s.d.)
- TRUST CONSTRAINT: global search problem for inequality Constraints (Yuan, 2015)

The results are as follows, on average

Table 4: Algorithm results in terms of success rate, average iteration number and objective function output.

Algorithm	Success Rate	Iterations	LCOE
COBYLA	95.88%	766	0.59
SLSQP	33.33%	3740	0.55
SHGO	100%	250	0.61
CP-SAT	100%	N.A.	0.92
TRUST CONSTRAINT	24.28%	898	0.77

Table 5: performance of the algorithms in terms of roof usage, investment usage and energy savings.

Algorithm	roof occup. %	Invest. usage %	energy savings %
COBYLA	25.15	79.86	48.9
SLSQP	17.41	56.2	33.52
SHGO	27.98	79.75	48.93
CP-SAT	49.57	74.38	25.25
TRUST CONSTr.	38.93	111.25	48.71

4.4 BMS Communication Validation

The BMS API has been validated in terms of integration for the inclusion of data. A number of tests have been performed using synthetic data, where a sample building has been created, being in a specific district, with a number of apartments, all being included in an acquisition campaign. Being integrated in the main website for data acquisition. Said data has been used in order to test the integration level of the BMS with the rest of the tools.

5 CONCLUSIONS

This paper highlights the successful development and implementation of the INSPIRE project toolset. The integration of the Advanced SRI Calculation Engine and the Optimized Investment Advisor has demonstrated its potential to enhance decision-making processes, optimize investments, and provide insights into a building's transition. Furthermore, the inclusion of the Continuous Tracking System enabled by a seamless BMS integration has opened a dynamic assessment and tracking of a building's smart readiness evolution. These insights can contribute to proposing a refinement of existing SRI frameworks, bridging the gap between static evaluations (Methods A and B) and a more dynamic, performance-based approach envisioned for future Method C by the EU Commission. Future developments will be addressed to enhance optimization algorithms and broaden system integrations to support diverse SRI-based business models. Finally, these tools have created a holistic framework that empowers stakeholders to achieve measurable progress in the ecological transition of buildings: by offering robust decision-making tools and scalable solutions, the toolset can facilitate sustainable building practices across various contexts.

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