Computer Aided Engineering of Cyber-Physical Information Gathering and Utilizing Systems

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***Abstract*—Engineering Cyber-physical information gathering and utilizing systems(CIGUS) presents the systems engineer with a difficult, multi-criterion, multi-objective decision problem. Research, development and design is done over many disciplines, across many domains, each with their specific models. Systems engineers are expected to provide a common level of communication amongst the domains to promote convergence to a design. We present novel information measures that enable combination of the underlying domain specific subsystems parameters in a way that makes the information yield of the system intelligible to decision makers and domain experts. These measures enable, for the first time, the application of multi-objective evolutionary algorithms and end-to-end computer aided engineering of CIGUS.**

Our novel approach is validated and verified through the application and direct comparison of simulated and experimental results of state-of-the-art weather radar network test bed designs. The approach resulted in Pareto optimal point within an average of 10% of the actual case study design parameters and within 25% of the Pareto ideal point. No additional parameters beyond the underlying domain parameters were introduced. This demonstrates that the computationally aided engineering approach presented in this work facilitates engineering feasibility decisions and the subsequent evolution of the engineered systems in way that reduces cost and effort.

***Index Terms*—information gathering and utilizing systems, cyber-physical, network sensors, multi-objective problem, optimization.**

I. Introduction

Interest in the engineering of cyber-physical information gathering and utilizing systems (CIGUS) has burgeoned in part due to the proliferation of wireless technology [1] and in part due to the growing demand for intelligible information. Such systems are complicated, with hierarchies of interfaces containing underlying complexity. They often involve distributed network sensors. The configuration can be dynamic, static and adaptive. Increasingly they involve real time collaboration among agents of varying degrees of autonomy. The interface of high yield systems often hides underlying subsystem complexity which pose new challenges to systems engineering[2]. Systems engineers are expected to provide a common level of communication amongst the domains of expertise that enable research, development and design of the system to converge. As the domains become highly optimized, the language and models become so specialized that it becomes extremely difficult to communicate across the domains. Prior to this work there was no practical and well founded way to combine the parameters of the underlying subsystems in order to represent the overall intelligible information yield. Moreover, in order for systems engineers to make the multicriteria tradeoffs and optimizations required for such systems, it is necessary to introduce new sets of objective functions without which existing multi-objective evolutionary algorithms[3], [4], [5], [6] can not be applied to CIGUS.

In the case of CIGUS, specific domain experts do the component subsystem design and subsequent modeling. Each of these domain specific subsystem models are developed in their particular domain language. Signal processing and communication models are essential to these systems. Weather Radar networks are a classic example. The sub-domains models involved in the systems engineering include; models of the component radars and their subsystems[7], network[8], signal processing[9], [10], and control[11]. What they have lacked is a systematic approach to overall optimization supporting the decision making process. The obstacle is combining parameters from different domains of expertise. The systems engineers ability to provide a level of abstraction that captures the entire system design problem at all levels will determine how quickly, or slowly, the design will converge to meet the requirements and how rapidly the systems will evolve. Clearly, for CIGUS, the underlying parameters and measures should resolve themselves in terms of the essential product: intelligible and useful information.

Moreover, CIGUS may be system of systems with uncertain and evolving requirements. Decisions made at multiple levels present a difficult multi-criteria, or multi-objective, decision problem. The systems engineer is presented with a difficult task of providing the decision makers with the information needed to support investment into further system evolution and development. By introducing information measures we are able to express the quality of the system in terms of more generally understood notions such as accuracy, precision, and bit rates as objective functions. We show that these objective functions, which encapsulate underlying domain specific parameters without introducing additional parameters. These can be combined with cost and throughput functions in a way that enables the application of state-of-the-art multi-objective evolutionary algorithms and automated decision support tools. Moreover, the predictions of this analysis can be directly compared with experimental data from test beds. One recent state-of-the-art weather network test bed, the Collaborative Adaptive Sensing of the Atmosphere (CASA) Integrated Project 1 (IP1), enables the comparison of simulations and experimental results presented in this paper and in more detail elsewhere.

II. Approach

To capture the salience of the engineered system, the systems engineer must separate the domain experts concerns, which are pursuant to providing objective content from the decision makers concerns, which are pursuant to ensuring that higher-level requirements are satisfied. While not conceived as such, a non-obvious example, rich in engineering challenges is the recently deployed the CASA IP1[12] experimental network of weather radars. The development is directed toward demonstration of the engineering feasibility of an end-to-end (TRL 6) [13] hierarchical emergency response and real time numerical weather forecast system. Its primary purpose is to improve tornado and severe weather warnings and to assist emergency management response to such events[12]. As a case study for demonstrating the need and effectiveness of extending multi objective analysis to the computer aided engineering of CIGUS and to improve the quality of high consequence technology transition decisions associated with their design and development, ”IP1”, has the unique advantage of being intensively and extensively reported in public documents and the open literature[12]. The present study thus provides a foundation for extending computer engineering aids to support and evaluate technical readiness decisions to cases where such information is not so readily available (e.g. SBInet[14]).

The design of complex sensor systems, such as weather radars and weather radar networks, was accomplished over years of exploration and iteration[15], [16] by multiple uncoordinated efforts. While this traditional process, which involves both trial and error and systematic design, has provided the sensor community with a new means of weather sensing and prediction[12], it cannot solve the present communication problem. One limitation of this approach is that it only allows for a temporary solution to a particular systems engineering problem that will need to be revisited as future requirements are introduced case by case. Here we present for the first time, the Pareto optimal multi-objective analysis of CIGUS. As we discuss elsewhere[17] this enables us to capture the evolution of a particular species of CIGUS over many generations. Various benefits such as: evolutionary context, reuse, accelerate development, and reduced risk.

While the primary and essential quality that is demanded of CIGUS is informativeness, *un*informativeness provides the principled way to construct quality loss functions. The theory underlying the present formulation is developed elsewhere[17], in this paper we present the salience of a specific application. Information produced by such systems is uninformative to the extent that it is already known, that is to say the *prior* or to the extent that it is *uncertain*. Up to now, genetic and evolutionary algorithms have offered or developed neither effective nor principled approaches to incorporating such priors and uncertainty. (Un)informativeness is key and well suited to the engineering of such adaptive intelligence oriented systems and systems of systems because it is directly related to the principle of maximum entropy[18] as pioneered by Jaynes[19] and subsequently developed[20], making the form of the engineering problem presented here intelligible in a way that enables the application of multi-objective evolutionary algorithms. Weather radar networks are particularly suited to our innovative approach because, although implicit, maximum entropy principle is embedded in the core signal processing formulation[21]. (Un)Informativeness provides a natural level of abstraction which fully respects and consistently subsumes lower levels such as those associated with traditional approaches to sensing, signaling and communication [9], [22], [23]. In this paper, we make use of the connection between maximum entropy and Shannon information theory to cast objective functions in terms familiar to the engineering community. This has the added benefit of separating the concerns of channel provider and content provider.

As shown in figure 1, sets of information oriented measures of the performance of sensor systems may be represented in components of an overall objective vector for purposes of evaluation and optimization. Work completed in [17] show how these measures abstract the sensor system estimators of the underlying parameters of the overall system in terms of virtual sensors. By extracting the relevant information from the underlying parametric signal models, expressed in terms of the language of the subdomain, experts enable a reduced set of information metrics that are most relevant to CIGUS. The complexity of the sensor networks considered here results in vectors with high dimensions that make it difficult for the decision makers to comprehend. Here we explore the effectiveness of using multi-objective genetic algorithms(MOGA) in concert with recent visualization advances for computer aided engineering to facilitate the decision making process that goes into the evolution of complex information gathering and utilizing systems, such as weather radar networks and particularly prospective adaptive networks.

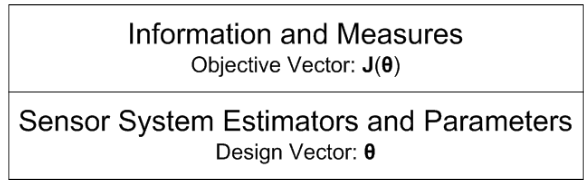

Fig. 1: The informative measures are abstraction over the sensor system estimators and parameters allowing integration over, and characterization of, a single or network of sensors. Objective functions formulated with informative measures capture the impact of varying parameters, design vector, on systems and networks of systems.

A. Information Oriented Objective Functions for Atmospheric Sensors

Information based objective functions enable channelization sensor information flows in accordance with the value and impact of the information. A virtual sensor is comprised of an element, called a test charge, that interacts with the environment that provides a measure of the stimulus, an element that receives the signal corresponding to this measure and a mediating element. In general, a phenomenological field, such as the weather, is sampled by sets of virtual sensors, each corresponding to a different measure and having its own characteristic channel.

The information oriented measures are built on the principles of maximum entropy and the concept of adaptive channel models that capture the scenes multiple spatial and temporal distributions. Adaptive channels model the interaction between the radar and test pattern, including propagation effects. The measures can be aggregated and stored in a data structure that consolidates all collaborative viewpoints on a common grid of vectors, containing all the utilizable information gathered from the scene[17]. The sensors may be mixed or fused at the channel level of abstraction enabling design and intensive optimization of diverse sensor networks.

A particular distribution of the phenomenological field salience and sensing instrumentation is modeled by a test pattern which represents a scenario from a set of viewpoints in support of requirements engineering

Scanning of test patterns by the simulated sensing system in space and time can be modeled as a graph traversal problem with the nodes representing subspaces to be sampled and the arcs weighed by the time cost. Each *subspace*, node on the graph, is a region defined by the beam solid angle, $\Delta\theta_s \times \Delta\phi_s$, and range extent, ΔR_s.

The objective functions used in the present work are chosen to explore the trade-offs between the conflicting objectives of information capacity, gathered information, quality of information, cost, and scan time.

The objective functions, $J_i(\theta)$, where the subscript i is the ith objective function, and θ is the design vector, are constructed for a typical weather scene as follows:

$$J_1(\theta) = \sum_{s=1}^{S} \left(I^s_{r_{cap}} + I^s_{v_{cap}} \right) \tag{1}$$

$$J_2(\theta) = \sum_{s=1}^{S} \left(I_{r_{cap}}^{HDs} \right) \quad (2)$$

$$J_3(\theta) = \sum_{s=1}^{S} \left(I_r^s \right) \quad (3)$$

$$J_4(\theta) = \sum_{s=1}^{S} \left(I_v^s \right) \quad (4)$$

$$J_5(\theta) = \sum_{s=1}^{S} \left(I_r^{HDs} \right) \quad (5)$$

$$J_6(\theta) = \frac{\sum_{s=1}^{S} \left(BER_r^s + BER_{\hat{v}_r}^s + BER_{\hat{\sigma}_{vr}}^s \right)}{3S} \quad (6)$$

$$J_7(\theta) = \sum_{s=1}^{S} \left(T_{subspace}^s \right) + \sum_{s=1}^{S-1} \left(T_{trans}^s \right) \quad (7)$$

$$J_8(\theta) = \text{cost}_{Rbase} + \text{cost}_{power} + \text{cost}_{agility} + \text{cost}_{antenna} \quad (8)$$

There are two classes of targets, six weather subspaces and six hard target subspaces. The information oriented measures of information capacity ($I_{r_{cap}}^s$ and $I_{v_{cap}}^s$), information (I_r^s and I_v^s), and Bit Error Rate ($BER_r^s, BER_{\hat{v}_r}^s,$ and $BER_{\hat{\sigma}_{vr}}^s$) are captured in equations (1)-(6). The superscript HD indicates hard target information oriented measures and the subscript s is used to identify the s^{th} subspace.

The first two objective functions, (1) and (2), sum the information channel capacity for weather and hard targets over the subspaces, respectively. Three types of information capacity, reflectivity($I_{r_{cap}}$), velocity($I_{v_{cap}}$), and hard target($I_{r_{cap}}^{HD}$), are defined instantaneously as the maximum bit rate that can be sustained by channel models of a gaussian white noise channel, and noiseless gaussian channel, and a Swerling 1 model channel, respectively[17]. The hard target velocity capacity is not calculated. In the present analysis the objective functions of channel capacity are minimized to ensure maximum capacity utilization.

Objective functions $J_3, J_4,$ and J_4 are comprised of the aggregated information gathered over the individual reflectivity, velocity, and hard target reflectivity channels, which are then summed over the subspaces, respectively. Hard target velocity information is not calculated. These functions are maximized.

The bit error rates are a measure of the quality of the information extracted and are a function of the errors in the underlying estimators. Objective function J_6 used in this analysis consolidated the BER associated with the various channels to provide an overall quality of information measure. The summation is over S, the subspaces, of the individual terms of each subspace referring to the reflectivity, (BER_r) the velocity ($BER_{\hat{v}_r}$), and the spectrum width ($BER_{\hat{\sigma}_{vr}}$). Hard target reflectivity or velocity bit error rate is not calculated. Minimizing the BER, maximizes accuracy and precision of the information[17].

Objective function J_7 is a measure of the total time it takes to acquire the information in the scene. It is a measure of the information gathering throughput of the system, the amount of information collected for the time to complete the test pattern scan. The time objective function is split into two summation, the first is the time to scan each subspace, the second is the time taken to scan between each subspace. The time to scan each subspace, $T_{subspace}^s$, is given by the dwell time of the radar, DT, and the number of positions in azimuth, $B_{az} = \frac{\Delta\theta_s}{\theta_{az_3dB}}$, and elevation, $B_{el} = \frac{\Delta\phi_s}{\phi_{el_3dB}}$, necessary to scan the entire subspace and the time to transition from beam to beam within the subspace. The time to move from subspace to subspace, T_{trans}^s, is given by rotating the sensor. Equations (9) and (10) define the subspace time and transition time.

$$\begin{aligned} T_{subspace}^s = B_{az}B_{el}DT + B_{el}\left[(B_{az}-1)az_{tB2B}\right] \\ + (B_{el}-1)el_{tB2B} \end{aligned} \quad (9)$$

$$T_{subspace}^s = az_{tS2S}^s + el_{tS2S}^s \quad (10)$$

where az_{tB2B}, and $el_{tB2B}$are the times to transition from beam position to beam position. In the case of the transition from subspace to subspace, az_{tS2S} and el_{tS2S}, the time is given by the angular difference in azimuth and elevation multiplied by the angular velocity in that direction. Minimizing J_7, maximizes the throughput.

Objective function J_8 is a measure of the cost of the system. The cost objective function, $J_8(\theta)$, is made up of four factors; *base radar cost, excess power cost, excess agility cost*, and *excess antenna cost*. Our initial objective cost function is a first approximation to the true cost function to be created and is referenced to the cost values for the IP1 weather radars[24], [12]. Cost is minimized.

In this study we chose the following decision variables: *maximum transmit power, half power beam width in azimuth and elevation, and maximum angular velocity of the pedestal*, given in table I to make up the decision vector, $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$. These variables were chosen because the object functions are most sensitive to them and are sufficient for validating the approach.

In the present case of computer aided engineering of a single radar we have reduced our objective vector, $J(\theta)$, to eight dimensions, corresponding to the six aspects of the scene about which we seek to gather information, the time interval over which we seek it, and the cost of the deployed system.

B. Multi-Objective Genetic Algorithms

Multi-objective optimization seeks to optimize problems that require the simultaneous optimization of multiple, often competing objectives [3]. Genetic Algorithms were originally developed to imitate the process by which living organisms evolve [4]. They have since been applied to multi-objective optimization problems as algorithms to supply reasonable approximations to the Pareto front and set [25]. Here they are used in a computer aided engineering approach to simulate the evolution of complex engineered systems. The technical analysis supports the decision makers in making a selection of a particular design out of the set of Pareto optimal designs. Each of the solutions returned by the analysis, see Figure 2, is a valid optimal design resulting from tradeoffs among the conflicting objectives reaching mutually non-dominated solutions referred to as the Pareto front. The discrete set of optimum points can then be used by the various decision makers to drive the evolution of the complex system being optimized, in this case a cyber-physical information gathering and utilizing system. The use of genetical algorithms to calculate the Pareto front and set of a multi-objective optimization problem is referred to as MOGA. Within the present approach we will demonstrate how MOGA can be used to calculate the Pareto front and set for low order models of a single weather radar. Higher order models can be incorporated into MOGA through the use of a more sophisticated simulation[17].

TABLE I: MOGA Settings

Decision Variables	Parameter (Unit)			
		lower	initial	upper
θ_1	Peak Power (W)	5e3	12.5e3	20e3
θ_2	$\theta_{az3dB}(deg)$	1	2	4
θ_3	$\theta_{el3dB}(deg)$	1	2	4
θ_4	Agility (deg/sec)	10	40	80
Cost Variables			Value	
R_{base}			$220e3	
λ_1			245	
γ_1			2	
κ_1			8e3	
λ_2			1463	
γ_2			1.5	
κ_2			20	
λ_3			736	
γ_3			1.5	
κ_3			4	

For these higher dimensional multi-objective problems, the present approach is an 8 dimension problem, a visualization technique called *Level Diagrams*[5] will be used to enable an improved analysis of the Pareto front and will provide an excellent tool for the decision makers. The Level Diagrams classify each Pareto front by the distance of the Pareto front from the ideal point, accounting for all the objectives simultaneously. It is extremely unlikely for an optimized solution to the Pareto front to achieve the ideal point[6], but we define the Pareto optimal point as the point with the shortest 1-norm distance from the ideal point. Every objective ($J_i(\theta), i = 1, \ldots, m$) is normalized and classified with respect to its minimum and maximum values on the Pareto front, $J_i^{norm}(\theta), i = 1, \ldots, m$ [5]:

$$J_i^{max} = \max_{\theta \in \mathbf{\Theta}_P^*} J_i(\theta), J_i^{min} = \min_{\theta \in \boldsymbol{\theta}_P^*} J_i(\theta), i = 1, \ldots, m \qquad (11)$$

$$J_i^{norm}(\theta) = \frac{J_i(\theta) - J_i^{min}}{J_i^{max} - J_i^{min}} \qquad (12)$$

such that,

$$0 \leq J_i^{norm}(\theta) \leq 1 \qquad (13)$$

The Y-axis on all the Level Diagram graphs, figure 2, corresponds to the value of the normalized objective function, and this means that all graphs are synchronized with respect to this axis. The X-axis corresponds to values of the objective, or decision variables, in physical units. Using this representation, all plots are synchronized with respect to the y-axis, meaning a single level on the y-axis returns all the information for a single point on any of the objective function or decision variables plots[5].

III. MOGA Analysis: Case Study

A. Scanning Analysis

The MOGA analysis is done with an agile mechanical pedestal using the decision variables and cost variables listed in table I.

The Level Diagrams of the Pareto front and set for the MOGA analysis of the agile mechanical X-band radar is given in figure 2. The Pareto optimal point is the light green square referenced by the arrow. Black vertical lines in plots of $J_7, J_8, \theta_1, \theta_2$ and θ_3 represent the specifications given in [24], [26] for the IP1 weather radars. Given the complexity of the multi-objective problem, it is surprising to see the Pareto optimal point coming in close comparison to the documented values of the IP1 weather sensing radar. The Pareto optimal point returns $\theta_{az3dB} = 1.6^o, \theta_{el3dB} = 1.9^o, P_t = 9.4kW$, cost $= \$459k$ and time $= 53sec$, compared to the IP1 values of $\theta_{az3dB} = 1.8^o, \theta_{el3dB} = 1.8^o, P_t = 8kW$, cost $= \$459k$ and heart beat time $= 60sec$.

TABLE II: MOGA Analysis Summary

	Power (P_t) (W)	θ_{az3dB} (deg)	θ_{el3dB} (deg)	Scan Time (sec)	Cost (k$)
Simulated	9359	1.6	1.9	53	458.6
IP1	8000	1.8	1.8	60	459.0

IV. Discussion

The present computer aided engineered approach applied to the given weather radar sensor results in a well formed high dimension Pareto front yielding the Pareto optimal point close to the ideal point. The 1-norm Level Diagrams, shown in figure 2, have smooth objectives with well defined minima where no single objective dominates, suggesting convexity of the Pareto front. Combined with location of the 1-norm Pareto optimal point to within 25% of the ideal point, we can characterize the Pareto front as well formed. Therefore, the Level Diagrams are providing insight into high dimension Pareto fronts when based on information oriented measures and test patterns.

The resulting Pareto optimal design vector yielded values, on average, in excellent correspondence with the actual IP1 design. An agreement between the optimal design vector and IP1 design of within 10% for the scan time is evidence that the current test pattern is a good representation of a multitask scene. Further indication is the similarity, within 10%, of the optimal azimuth and elevation beam width to the IP1 design. The Pareto optimal peak transmit power, a relatively outlier at 18% greater than the IP1 design, is a result of the magnetron transmitter in the IP1 radar operating below its maximum rated peak power. The present computer aided engineered approach accurately models the evolution of IP1 system.

Although the results exhibit excellent convergence, extending the objective vector to include a reliability/availability component would likely result in further convergence between the Pareto design and real case. However, a valid and verified reliability/availability model for the present case under study has not appeared in the literature. As the models become available, they can be incorporated into the multi-objective optimization aiding in the engineering of the system.

The computer aided engineering approach provides isolation from the other objective functions allowing higher level models for cost, reliability, maintainability, volume manufacturing, industrial learning curves, and other potential non-functional and functional requirements to be readily incorporated or modified. MOGA simultaneously evaluates each of the objective function individually. This allows the objective functions to be individually modified without the need to update subjective weights. The additional abstraction of the informative objective functions allows the inclusion of uncertainty and priors into the MOGA analysis and encourages the use of other multi-objective evolutionary algorithms(MOEA) that may be better for other applications.

The method presents an approach allowing for the acceleration of the evolution of complex, multi-criterion information gathering and utilizing systems. Extension to higher order models of signal estimators and test patterns in the presence of multiple weather sensors is of interest to provide insight into design trades over changing weather conditions and different venues. Specifically, creation of higher order models of the sensor system and test pattern will facilitate exploration into the trade space of polarimetric weather radar networks and waveform design for network multifunction radars. Moreover, the

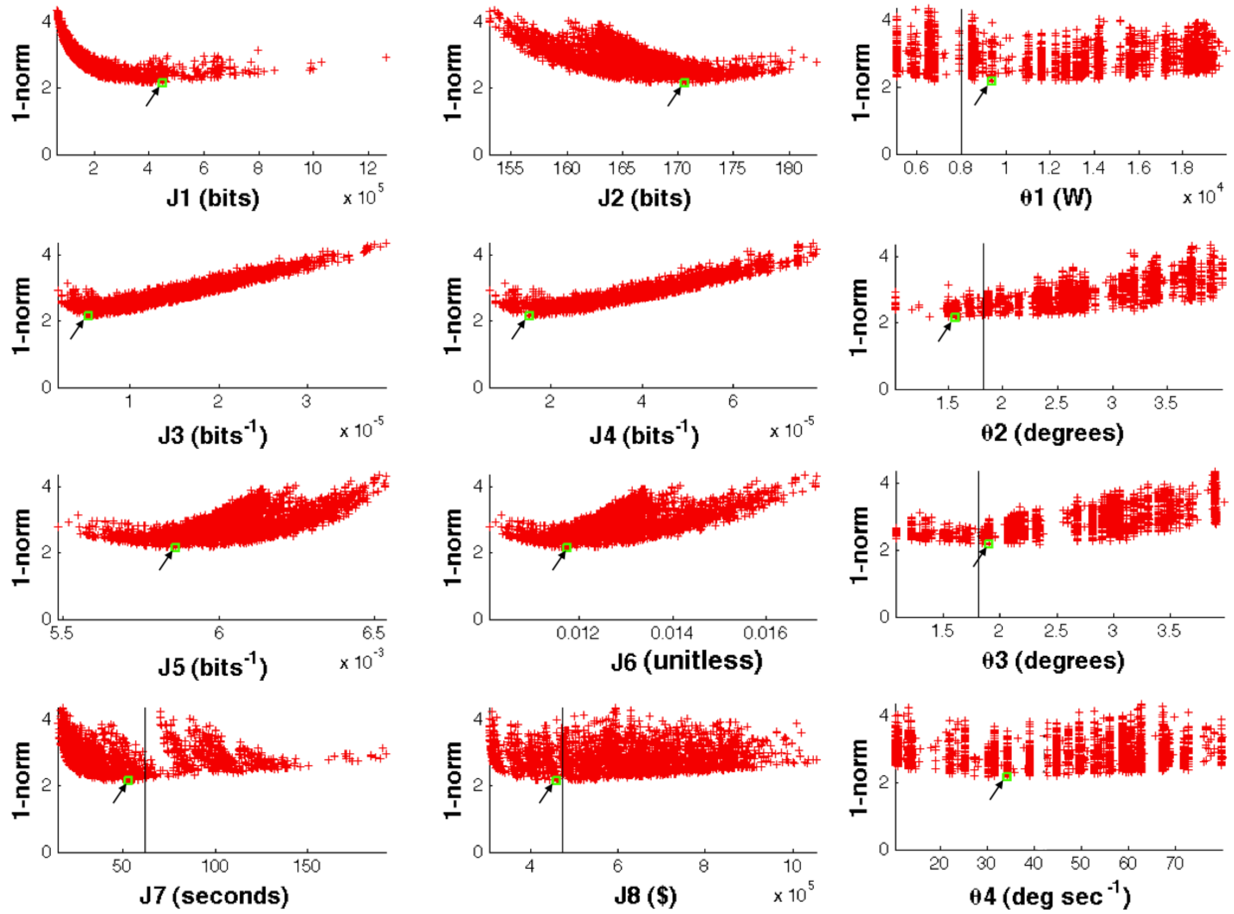

Fig. 2: 1-norm Level Diagram of the Pareto front and set the eight objective functions comprising the objective vector, $J_i(\theta)$, where the subscript i is the ith objective function, and θ is the design vector used in the MOGA analysis of the case study X-band weather radar described in section III-A. The Pareto optimal point is the light green square referenced by the arrow. Black vertical lines in plots of $J_7, J_8, \theta_1, \theta_2$ and θ_3 represent the specifications given in [24], [26] for the IP1 weather radars.

method can be extended to incorporate further decision support for more complex trade-off analysis that may be required to assess the evolution at higher levels to support business modeling and planning.

V. Conclusion

We have shown that by introducing integrative objective information oriented measures, we can define a level of abstraction which captures the underlying sensor estimators and parameters that solves the communication problem between the systems engineers, domain experts and decision makers. Not only will the obstacle be eliminated, the design of these complex sensor systems will converge much more rapidly, allowing for an acceleration in the evolution of the systems, with the inclusion of the preferences of decision makers a posteriori to the objective analysis, hence acknowledging subjective influences.

The analysis is applied to weather radar designs providing complex multi-objective design problems with evolving specifications and requirements. Without any adjustable parameters, any subjective weighting, and in such a complex design space where a multiplicity of results could have occurred, the informative methodology of systems engineering resulted in decision parameters very close to that of the IP1 system. The results of the MOGA analysis case study, show that the approach is successful in modeling the complex system by producing a Pareto optimal point within an average of 10% of the case study's design specifications and providing an objective basis for evaluating the engineering feasibility of the end-to-end system and its transition into operational environments for further development.

The foregoing capabilities facilitate the demonstration of engineering feasibility and subsequent development and evolution of the CIGUS. We develop objective functions, combining measures of cost and throughput with the underlying domain specific parameters, enabling the application of state-of-the-art multi-objective evolutionary algorithms and automated decision support tools. The novel systems engineering approach is further validated and verified by the agreement of the predictions of the analysis and the experimental data from the IP1 test bed. Clearly, in the case of weather radars had the present approach been available, considerable time and money could have been saved[17].

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